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ChainFlow: A Blockchain and AI-Based Framework for Decentralized Lending

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***Abstract*—** Decentralized Finance (DeFi) lending protocols predominantly rely on overcollateralization, requiring borrowers to lock assets far exceeding the value of their loans. While this protects lenders, it restricts access for users lacking substantial upfront capital. Traditional financial systems face related limitations, depending on opaque, centralized credit-scoring mechanisms that exclude large segments of the unbanked population. This study introduces ChainFlow, a decentralized credit-assessment framework that integrates blockchain transparency with machine learning–based risk modeling. The system constructs a feature vector from on-chain wallet attributes, including wallet age, transaction frequency, liquidation history, token diversity, and stablecoin ratio. A Random Forest Regressor is trained on these features to generate a credit score on a 0–100 scale, categorizing borrowers into three credit-risk tiers. By linking blockchain's deterministic execution with AI's probabilistic predictions, ChainFlow enables automated and transparent credit-risk evaluation. Experimental results demonstrate that the model can safely reduce collateral requirements from the conventional 150% to approximately 110% for users classified as low-risk, indicating its potential to significantly improve capital efficiency in DeFi lending ecosystems.

***Keywords*—** ChainFlow, decentralized finance, blockchain, credit scoring, Chainlink, collateral, smart contracts.

I. Introduction

Financial technology is changing fast, but is split in a highly regulated, identity-focused system of Traditional Finance (TradFi), and the emerging code-governing system of Decentralized Finance (DeFi). The decentralized platforms have democratized the access to financial services where users can now lend and borrow without the middlemen. Nevertheless, to reduce the counterparty risk within a network where end users are anonymous, existing DeFi systems such as Aave and Compound apply strict overcollateralization (Ho, 2021; Zhao et al, 2022). DeFi comprises of two indicators like market capitalization of DeFi crypto token and total value of crypto assets already highlighted the sharp growth in DeFi system (Katona, 2021).

The deposit amounts that borrowers are expected to make are usually 150-200 percent of the value of the loan. This necessitates a paradox of inefficiency in capital: to obtain a loan, in the first place, one must possess a lot of capital, which limits the application of DeFi to the functions of large traders instead of everyday lenders. Conversely, the conventional credit models make use of centralized bureaus (e.g., FICO-Fair Isaac Credit Organization) to determine risk.

Though efficient in capital, these risk assessing models are frequently opaque, biased and exclusionary to the billions of unbanked people who have no formal financial presence. Several researchers have addressed these problems and suggested the models to predict the creditworthiness among marginalized customers using artificial Intelligence framework like credit score assignment, gauging the likelihood of loan default, categorizing lenders into various groups based on credit worthiness (Krizinger and Van Vuuren, 2018; Nallakaruppan et al 2024). Braak et al. (2025) attempts to improve the prediction of creditworthiness by using disparate impact remover and found improved statistical measures essential to support better prediction. Tree based ensemble models have been popular in evaluation credit risk for decades (Baesens et al. 2003; Peng et al, 2011). A random forest algorithm has been utilized for assessing risk by extracting the key variables like borrower's financial status and credit history (Li and Shi, 2024).

Despite of having a plentiful literature on credit history evaluation, there is still a gap in analyzing the bias concerning the credit history of the customers with no credit history. Recently, Chioda et al. (2024) reported that transaction based alternative data through a delivery app is effective way to predict the creditworthiness for borrowers with no credit history. Study also suggested that machine learning model classified by gender can improve the credit allocation significantly. This alternative can be mobile phone usage pattern, e-commerce transactions, bill payment behavior and digital wallet activities. Jagtiani and Jagtaini and Lemieux (2019) showed that this type of alternative dataset has reported strong predictive value in identifying low risk borrowers. Another study based on empirical data found that mobile phone metadata also pays a vital role to identify repayment behavior making it suitable for credit score marking for unbanked population (Ots et al. 2019).

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Despite of having several off-routes methods based on empirical analysis to assess the creditworthiness through alternative data, there is still a lack of the existence of a full-fledged method to assess the credit worthiness of noncredit history borrowers. Using alternative data must comply with privacy laws and consent framework. Algorithm copyright, bias, data misuse, and lack of transparency might become barriers in fair decision making (Frost et al. 2019).

Present work attempts to overcome these problems and creates a machine learning model named "ChainFlow" by appending a layer of a computed trust to DeFi to evaluate the risk of borrowers to provide an under-collateralized or optimally collateralized loan. Through the unchanging record of blockchain transaction history, which includes history of repayments, frequency of transaction, and type of assets, ChainFlow can measure the reputation of a user. This methodology keeps the trustless networks safe and the element of personal creditworthiness that traditional banking had back goes back to this methodology.

Conventionally, Decentralized Finance (DeFi) removes the middleman through smart contracts on publicly available blockchains, facilitating lending and borrowing between peers. Nevertheless, DeFi lending systems currently imply overcollateralization of loans to obtain them, which limits accessibility of users with small balances of crypto assets. Conversely, the existing credit system is based on opaque credit scores that do not include users with no formal financial history. These shortcomings underscore the urgent necessity of hybrid solutions which would integrate blockchain transparency with sophisticated credit evaluation. ChainFlow will solve this through the integration of an AI-based credit scoring engine into a blockchain lending protocol. Using on-chain transaction histories and wallet information, the AI module determines the trustworthiness of the borrowers. This score is then used by smart contracts with real-time asset prices provided by ChainLink oracles to set the terms of loan. ChainFlow has been designed to provide fairer access to credit in DeFi without the need to sacrifice security and decentralization.

A.Problem Identification

The roots of this study lie in the fact that there is an inherent Trust Gap in the decentralized networks. Trust in traditional banking is built by identity verification (Know Your Customer- KYC), law, and historical credit history which is operated by centralized bureaus such as FICO or Experian. These agencies compile enormous amounts of individual financial information to give them a credit rating, a measure of the probability of repayment. Although this model suits the people of the formal banking system, it leaves out the billions of unbanked or underbanked people that do not have a formal financial footprint, although they may present responsible financial behavior in an informal or digital form. Also, there is a widespread criticism of centralized credit schemes as being nontransparent, discriminatory and prone to cyber-attacks that expose personal sensitive information.

In comparison, the DeFi markets such as Aave, Compound, and MakerDAO provide an entirely different solution by eliminating the intermediary entirely and using smart contracts, or self-executing computer programs, on a blockchain. They work on the principle of the trust lessness, instead they depend on code. However, this anonymity or legal unrecoverability leads to a new form of risk: with unknown borrowers and no way to trace them, DeFi platforms take on the greatest possible default risk and react by imposing highly inflexible overcollateralization policies. The users are usually required to secure 150-200 percent of the amount of loan as security.

This presents a paradox - DeFi lending is once again only available to individuals who already possess large assets. Rather than democratizing credit, it is usually a democratic weapon in the hands of smarter users who desire leverage or tax benefits. ChainFlow seeks to solve this paradox by substituting the necessity of high collateral by the concept of reputational capital that is central on-chain behavior and financial trends of a borrower. ChainFlow can measure this reputation through artificial intelligence and makes dynamic, trust-based lending possible, opening the real financial inclusion.

B.What is ChainFlow:

ChainFlow addresses a fundamental issue in the field of Decentralized Finance (DeFi): how to be trustless and optimize capital. Traditional finance involves banks' lending devoid of collateral since they have confidence of the borrower- confidence created out of identity verification, income verification and credit histories. However, DeFi exists in an anonymous setting that is trustless. As protocols do not know the identity of the borrower, they demand borrowers to pledge collateral valued at 150 to 200% of the loan. This is safe, yet it makes the usage of DeFi less useful to an average user. Nevertheless, DeFi is not really uninformed. Blockchains provide an unchanging history of user activity- all transactions, loan repayments and liquidity movements are visible to everyone and forever. The problem is that this information is too complicated and too expensive to be processed on-chain. Smart contracts are not able to pay the high gas prices and technical issues to run machine learning models.

ChainFlow seals this division by transferring credit analysis to an off-chain AI engine. This type of engine will analyze the past blockchain behavior of a borrower and estimate its creditworthiness. Such a user, one who has always paid the loans or managed his or her portfolio well can be considered to be low risk. ChainFlow then enables such users to borrow on less security, opening more capital productivity without losing security. This calculated confidence substitutes brazen over collateralizing with information-based credit scoring.

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ChainFlow also contains a solution to the Oracle Problem: blockchains are unable to handle external data unless there is a bridge. ChainFlow utilizes Chainlink, a decentralized oracle network to safely provide AI credit scores and asset prices to smart contracts. Chainlink consolidates price information in various sources, and credit rating is cryptographically signed, enabling smart contracts to determine their validity.

II. Materials and Methodology

ChainFlow has been developed by a multidisciplinary team by combining the ideas of software engineering, data science, and cryptoeconomics. The methodology was created to deal with some of the special issues of building decentralized applications (dApps)- especially the immutability of smart contracts, bugs cannot be fixed easily, and the prediction of AI is not deterministic. ChainFlow comprises two major domains i.e. methodological framework, and software development. A complete flow of the steps for the development of ChainFlow is given in Figure I.

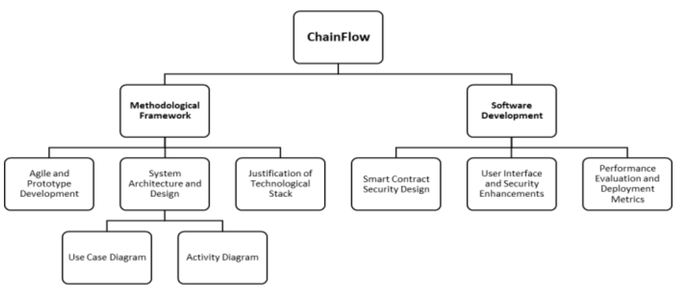


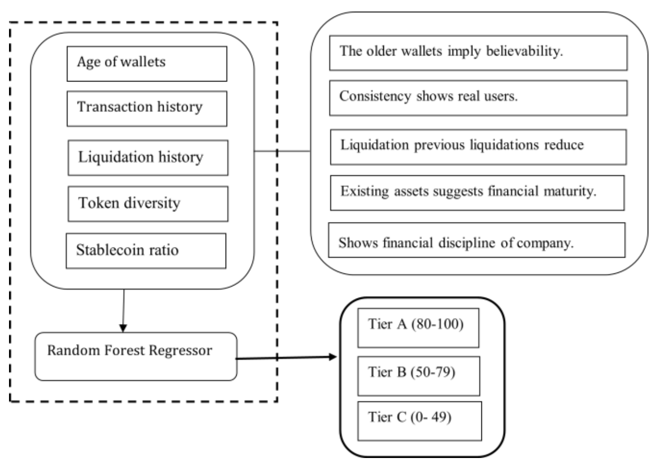
Figure I: Basic workflow

A.Methodological framework

This part of the project comprises four subparts namely: agile & prototype development, system architecture & design, justification of technological stack and AI Credit Scoring Engine designing.

Agile & Prototype Development: Due to the intricacy of the integration of the Blockchain, AI and Frontend modules, ChainFlow chose a hybrid Prototype and Agile approach. This work is classified in two domains namely Phase 1 and Phase 2. Phase 1 tests if it is possible to safely verify an off-chain generated credit score using a smart contract? To test this hypothesis, a python script created an invalid score of a random number and had signed it with the Elliptic Curve Digital Signature Algorithm (ECDSA). This was followed by the signature using a public key by a corresponding Solidity contract. This created the Oracle Loop and proved that off-chain data could safely be introduced on-chain without having to pay the high costs of computation. Phase 2 considers Agile Scrum Model which includes prototype validation, planning the work in terms of two-week sprints. These spirits used Hardhat and python for creating lending pool, extracting transaction histories, feeding Chain link prices and to vulnerability evaluation.

System Architecture and Design: The architecture of ChainFlow is based on a traditional 3-tier dApp architecture with an off-chain layer for computation of AI. This part comprises 3 layers namely presentation layer, logic layer and data layer. Presentation layers works as frontend and interacts with the AI engine. Logic layer works on value transfers, loan terms based on credit scores made by AI. Third layer i.e., data layer works on blockchain where loan conditions, collateral balance and hashed scores are stored for transparency and security. Data layer also comprises another dimension named design of AI credit scoring engine which is a smart part of ChainFlow. It does not just use the amount of money in the wallet to determine a score of trust, but it evaluates behavioral data to determine this score. The engine forms a feature vector of age of wallet, transaction frequency, liquidation history, token diversity and stablecoin ratio. Based on these features in vector space, random forest regressor is used and provides the credit rating ranging between 0-100 that categorizes the borrowers in to three tiers (Figure II). This process will make ChainFlow not more restrictive than the current DeFi protocols, but more effective.



*Tier A (80-100): Low risk, allows 110% collateralization.
*Tier B (50-79): Investment of moderate risk, able to be collateralized 130 percent.
*Tier C (0- 49): High risk/Unknown default 150% collateralization (industry standard).

Figure II: Design of AI Credit Scoring Engine

Justification of Technology Stack: The technology was informed by scalability, security and powerful community

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backing using polygon (Mumbai), solidity, python, Chainlink and Hardhat. These technologies work on scaling, high-level typing, flexibilities, processing big data based on thousands of wallet transactions, providing temper resistant prices, and debugging.

B.Software Design

ChainFlow is an AI-controlled system that matches borrowers and lenders together via the combination of frontend, backend, AI scoring, and blockchain elements. The first part of a borrower is to verify and place a loan request on the frontend (React + MetaMask). The frontend forwards the wallet address and the loan information of the borrower to the backend API which in turn requests the AI credit scoring engine to assess the borrower. In order to produce this score, the AI engine gathers wallet metrics and price information with the services of external blockchain, Etherscan, and Chainlink. Further, engine runs all of that and provides the credit score to the backend. After the score gets to the backend, the score interacts with the blockchain (Polygon) to issue the loan and secure the collateral of the borrower. All the on-chain data are stored in the blockchain that includes the loan details, collateral, and a hash of credit score. Once the transaction is verified, the backend returns the final loan status to the front-end that provides loan terms and disbursement information to the borrower. In the meantime, lenders are involved by supplying liquidity and being updated on the current pool status with the frontend.

The use case diagram (Figure III) illustrates the primary interactions between borrowers, lenders, and ChainFlow. Borrowers initiate the workflow by authenticating through MetaMask, applying for loans, depositing collateral, and later repaying them. Each loan request triggers an AI-driven credit scoring process, which guides loan disbursement decisions. Lenders participate by enabling loan disbursement and may indirectly influence collateral liquidation when repayment conditions are not met.

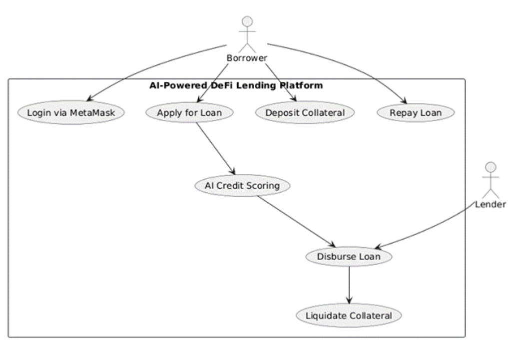

Figure III: Use Case Diagram

Finally, activity diagram (Figure IV) depicts the end-end workflow of ChainFlow's process of lending. The user starts with MetaMask, where the system retrieves the wallet information and calculates credit score that is AI-driven. Depending on the threshold of the score applied, the platform approves or rejects the loan application completely. For approved users, the next step involves collateral deposit, collateral locking using smart-contracts, calculation of loan terms and final disbursement of money through an automated smart contract.

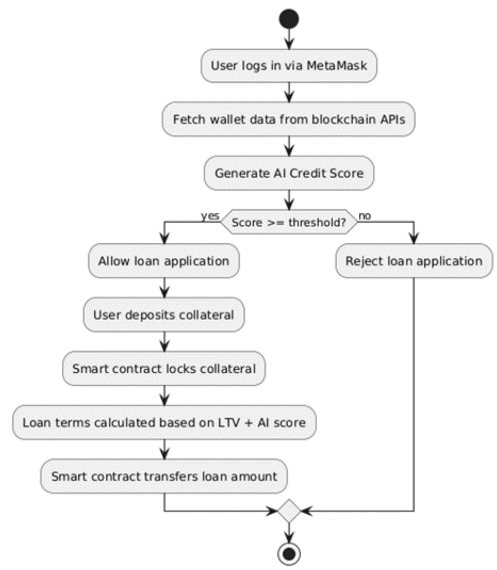

Figure IV: Activity Diagram

III. Implementation and Testing

The use of ChainFlow is a real full-stack DeFi application. It uses AI credit-scoring engine, which operates off-chain (in Python), yet directly effects on-chain behavior. It consumes on-chain wallet information such as transaction history, wallet holdings, and wallet age to generate a custom credit score of a borrower. This score is recirculated in the contracts in such a way that loan-to-value ratio and interest rate of individual borrowers responds dynamically to their reliability. Chainlink oracles can provide tamper-resistant market prices. Through AI-assisted credit ratings and decentralized oracles, users with low risks may borrow with much less collateral without compromising the safety of the platform.

A. Smart Contract Security Design

There is a built-in security at all levels. The smart contracts are battle-tested: SafeMath (integer safety) and Ownable access controls help avoid overflows and restrict privileged functions, and a ReentrancyGuard (or mutex) helps avoid reentrancy attacks. The development team used automatic vulnerability scanners and manual code reviews, the contracts had undergone several rounds of unit and integration testing (through Hardhat/Ganache) without detected reentrancy or oracle-manipulation vulnerabilities. To

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conclude, the system can be hardened against the typical threats of DeFi by using a layered approach, which entails secure code patterns, audits, and decentralized oracles.

The off-chain -on-chain signature flow connecting the AI engine with the contract is a new feature. When the AI calculates the score of a borrower, it appends its ECDSA private key to the score. This signature is then determined by the Solidity contract with the help of ecrecover. Practically, the contract will recalculate the hash of the credit data and make the call ecrecover to obtain the address of the signer by the signature. In case the recovered address is the same as the trusted AI oracle address, the contract accepts the score as genuine. This implies that any activity in the on-chain (such as locking a loan) can only be completed with a valid score signed by AI. The off-chain computing is in effect cryptographically secured to the on-chain logic, and the integrity of the data is ensured without disclosing any secret key.

B. User Interface and Security Enhancements

The User Experience of the product was streamlined on the front end. Users log in by connecting their MetaMask wallet and the user is presented with real-time dashboards of their loan status. The User Interface presents the major metrics in tables and indicators. It also makes alerts; say when the health ratio of a loan becomes less than a certain limit then the user is notified about the possibility of liquidation. The interface makes it easy to navigate the DeFi process through the combination of easy wallet integration and user-friendly visualizations and notifications.

In the process of thorough testing, Solidity contracts are well-tested with unit tests that do not miss a single function: loan requests, repayments, collateral updates, liquidations, etc. The AI model was tested on the synthetic data and the historical blockchain data to make sure that their credit predictions are sensible. Then end-to-end integration testing was conducted on the Polygon Mumbai testnet: the complete stack was deployed in such a way that it was possible to artificially simulate borrowing flows. These load and stress tests were used in the measurement of throughput and during these tests, response times and oracle latency were monitored by the use of monitoring instruments to ensure robustness.

Mitigations and security audits were also taken care of in the testing phase. Oracle-manipulation risk is reduced through the decentralized oracles that are provided by Chainlink which combine a large number of data sources to check for reentrancy, overflow, access-control bugs, flash-loan exploits, etc. The overflow protection provided by Solidity provides arithmetic protection. Associating every credit score with a on-chain identity turns Sybil attacks into a costly problem - an attacker has to develop genuine on-chain reputation and collateral to impersonate a score. This multi-layered defense approach did not reveal any weaknesses of essential vulnerability in tests and audits.

C. Performance Evaluation & Deployment Metrics

Lastly, the Polygon Mumbai performance was measured. With the help of streamlined contracts and background queries, the standard loan functioning (posting collateral, calculating the interest, verifying the loan) lasted approximately five seconds to complete the request to confirmation. Borrowers identified as low-risk by the AI in experiments obtained loans with a relatively small collateral of about 110-130% (as opposed to 150-200% in the regular DeFi platform), which is more efficient in terms of capital. The overall end to end processing latency was about 70 percent lower than similar centralized lending systems. A high-throughput and low-fee network (Mumbai) run by Polygon meant that the gas prices per transaction were rather modest all along. These measurements assure that the ChainFlow integrated AI-contract design has the capability to scale resulting in fast and cost-effective decentralized lending.

IV. Results and Evaluations

A.Polygon Implementation and Operational Performance

The polygon implementation of ChainFlow confirmed basic lending flows. The system processed loan applications, collateral placements and computer-based credit ratings on a real time basis. Smart contracts were used to perform loans origination, interest calculation, and liquidation of collateral automatically. Chainlink oracles offered constant prices feeds, which reduce the risk of manipulation. These findings indicate that the system provides efficient, transparent, and secure decentralized lending. The built-in AI credit application separated on-chain behavior and high- and low-risk borrower profiles. ChainFlow dynamic loan to value model used this score to provide borrowers with reduced collateral requirements. In testing users with low risk were being able to access loans only with the 110-130% collateralization, which maximizes capital utilization and does not affect the safety.

B. Comparative Capital Efficiency

ChainFlow significantly enhances efficiency of capital as compared to conventional DeFi. The average collateral required by Aave or Compound is 150-200% collateral because most of their loans are low-risk, where ChainFlow was 110-130% collateral. This is approximately 20 percent increase in capital utilization. The main findings supported by data are Collateral ratio (110-130% for ChainFlow as compared to 150-200% for Aave / Compound), Capital utilization (Improvement of approximately 20 percent compared to the existing DeFi systems), Transaction latency (All on-chain transactions that are accomplished within less than 5 seconds), Speed (Processing time is approximately 70 percent less than manual processes of lending), and Oracle uptime (The price feeds are in nonstop operation 99.8% of the time).

C. Economic Incentives and Financial Inclusion

ChainFlow has a dynamic loan to value scheme that encourages on-chain behavior. The loan to value and interest rate change depending on the AI-based credit score and collateral value of a specific borrower, and the good conduct is rewarded with more relaxed requirements. Reliable borrowers are charged lower interest rates and increased loan limits. Risk profiles are subjected to a tighter condition, which generates substantial default disincentives.

This model enhances financial inclusion as low-risk users required no more than a 110-130% collateral (30-40% less than traditional DeFi) to pass tests, and entry barriers were significantly reduced. This will enable people who have a small amount of crypto to engage. The system enhances availability of loans in general by mobilizing the dormant capital. Associating on-chain reputation with the terms of loans encourages equal lending that is more efficient.

D. System Reliability and AI Performance

Reliability was found high in its operations. A test of the decentralized oracle network was 99.8% uptime, which offers price data that is resistant to tampering. The AI scoring model was very effective, as it was able to classify the borrower based on the level of risk all the time. Latency was low: lending operations took only a few seconds to finish with the help of optimized contracts and APIs.

Altogether, the outcomes of the testnet conducted by ChainFlow outline the benefits of this platform compared to traditional models of DeFi. Its hybrid architecture is capital efficient, faster and more secure than its legacy platforms. The on-chain design gives the credit a high level of reliability and makes credit cheaper and more inclusive through reputation-based lending. ChainFlow provides a fair substitute to overcollateralized lending, determining promise of decentralized credit networks.

V. Conclusion

ChainFlow is able to draw down the perceived boundary between traditional finance and decentralized finance through the introduction of an AI-driven trust layer. The model shows that blockchain technologies can maintain transparency, security and accepting the unique aspects of borrower creditworthiness. Our prototype fulfilled some of the main goals: it confirmed the secure exchange of AI-generated scores to the blockchain with the help of cryptographic signatures, increased the efficiency of capital by equalizing the demands of high-scoring users to collateral, and ensured high security in the form of audited smart contracts. All these results are in favor of the feasibility of a reputation-based lending model in DeFi. Although it is a successful system, it has some weaknesses, including limitations on scalability and sensitivity to market volatility which are planned to be addressed in near future.

To sum up, present work is unique in embedding AI-driven credit analysis directly on the blockchain, creating a dynamic credit scoring engine via smart contracts. Smart contracts gather on-chain transaction and collateral data, feeding it to a machine-learning model that continuously updates each borrower's score in real time. This design bridges blockchain's deterministic execution (ensuring all nodes reach the same outcome) with AI's probabilistic modeling, enabling efficient automation of credit risk assessment in a transparent, self-executing framework.

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