

Financial Advisory & Credit Scoring System For Small Income Individual

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Abstract—Personalized, explainable, and adaptive intelligence is not generally present within financial decision-making for individuals or small businesses. Current digital finance platforms often emphasize the tight coupling of static user profiles and machine learning models. This paper presents a moment-based financial advisory platform built on a microservices architecture, where periodic financial conditions are converted into interpretable financial indicators through a dedicated feature engineering module. The proposed platform is separate from data ingestion to feature calculation and financial intelligence, making way for a more seamless incorporation of future AI models into credit scores and recommendations. Experiments conducted on synthetic data sets illustrate the correct functioning of the proposed architecture. The proposed platform is aligned with Sustainable Development Goal 8 (Decent Work and Economic Growth), as it fosters economic stability, productivity, and inclusion.

Keywords—*Financial Advisory Systems, Feature Engineering, Microservices, FinTech, Explainable AI, Credit Scoring.*

Introduction

The process of financial planning together with credit management creates essential financial structures which affect both individual economic health and the existence of small enterprises and startup businesses [12]. The recent years have seen digital financial applications become more popular because they provide users with easy-to-use financial tools which include budgeting tools and credit monitoring capabilities and investment planning resources [6]. The platforms have gained widespread use but they cannot deliver effective financial support because their design depends on fixed user information together with hidden machine learning systems [1]. The system needs to handle financial behavior changes since people need normal recommendations, which they can easily understand, to follow [2].

Artificial intelligence tools now enable automated investment advisory services together with credit risk assessment systems [10], but these systems depend on organizations to provide their financial data in a structured and understandable way [3]. Real-time decision-making becomes impossible because traditional financial datasets contain data that either lacks consistency or needs proper organization [5]. The system creates essential obstacles which prevent users from adopting the system because small business owners and individuals need to receive simple insights instead of advanced predictive results [7]. The research develops a financial intelligence system which uses snapshot-based technology to record financial statuses of both individuals and businesses and convert them into valuable financial metrics. The system uses discrete financial snapshots which demonstrate how income patterns and spending habits and asset growth and debt obligations and credit usage evolved through different time periods instead of following the continuous financial history used in traditional systems [3]. The system uses financial snapshots to conduct long-term health assessments which help it discover different financial trends and unusual occurrences and typical human behaviors across multiple time periods. The research presents a key advance through the creation of a financial snapshot data model which enables time-based analysis of financial conditions. The model establishes periodic financial states for financial information which enables better financial progress monitoring and generates adaptive recommendations that respond to changing economic conditions. The system implements a microservices-based backend architecture which enables its various financial analytics components to expand and work together with independent modules. The research establishes a specialized financial feature engineering layer which converts raw financial data into indicators that AI systems can use for analysis in the targeted domain [8]. The engineered features of the system provide additional transparency to the model while enabling users to comprehend the financial recommendation system through explainable AI features [2]. The system achieves its financial inclusion target through its ability to foster user confidence through its interpretable design while implementing responsible economic development targets. The proposed snapshot-based finance intelligence system combines temporal financial modeling with modular system architecture and explainable analytical capabilities to deliver personalized financial guidance which adapts according to user needs while supporting sustainable financial planning and credit management practices [9].

Literature Survey

Financial advisory systems research currently concentrates on predictive modeling methods which include credit scoring models and portfolio optimization frameworks and fraud detection algorithms [11]. The models successfully predict outcomes yet they depend on extensive machine learning systems which use deep learning structures that do not allow users to comprehend their functioning [10]. The use of non-explainable models creates obstacles which prevent users from adopting systems and which hinder regulatory bodies from approving financial decision-making processes that require transparent operations [2]. The introduction of Long Short-Term Memory (LSTM) networks together with Transformer-based architectures has advanced deep learning techniques, which now provide better prediction results for credit risk assessment and investment recommendation systems [10]. The models function as black-box systems which show their results without explaining the reasons behind those results [1]. The absence of explainability creates a substantial constraint which affects financial environments, because users need to know how recommendations originate before they can trust them [2]. The development of Explainable Artificial Intelligence (XAI) methods has not achieved its purpose of better transparency, because these methods get implemented through integrated system designs which prevent future system changes and expansions [2].

The development of robo-advisory platforms created automated systems which manage investment portfolios and handle investment management tasks [6]. The systems optimize asset allocation strategies but they concentrate on investment performance which fails to process or display essential financial behavioral data in a structured way [6]. The majority of personal finance management applications provide basic functions for transaction tracking and budget creation and expense classification while they fail to deliver domain-specific financial indicators that show an individual's complete financial status [9].

Research on feature-first modeling methods in financial intelligence systems remains limited because these methods use financial indicators that can be easily understood before they apply machine learning techniques. The raw transactional data converts into structured data elements which include savings consistency and liquidity ratios and credit utilization patterns and expenditure volatility, making it possible to get better understanding to downstream AI models [8]. Financial technology research shows that modular systems and explainable artificial intelligence have become essential components for success yet current systems fail to provide distinct processes for creation of financial elements and development of predictive capabilities [2]. The proposed system addresses this research gap by introducing a feature-oriented, AI-friendly system architecture that bridges traditional financial data processing with future machine learning integration. The architecture uses microservices-based design to separate AI-based decision-making components from the processing of financial indicators. This separation

facilitates independent development, scalability, and the seamless incorporation of explainable machine learning models without requiring modifications to the underlying data processing pipeline. The system delivers a flexible platform which developers can use to create financial intelligence applications that provide transparency and adaptability and meet user needs in today's financial systems.

Methodology

The proposed project will create an online finance intelligence platform which serves as a backend system to assist both individual users and small business operations [12]. The platform processes financial data which it collects through its system to store data securely while enabling client applications to access its functions through RESTful APIs. The system enables users to enter financial data which researchers will examine using the system's analytical modules through its structured API design that connects user interfaces to backend services. The backend computational services analyze user-submitted financial data to produce structured recommendations which consist of actionable financial decision insights and risk avoidance strategies and improvement opportunities based on the user's financial condition [9].

The system uses a sequential workflow based on microservices which enables you to achieve your design goal of modularity and scalability for your snapshot-based advisory architecture. The security service uses JSON Web Tokens (JWT) to manage user authentication and authorization which safeguards financial resource access for users. The system creates a financial snapshot after successful user authentication, which documents essential economic details about income, expenses, assets, liabilities, and established financial objectives [3]. The financial snapshot which shows the user's present financial condition will be stored in a relational database system to maintain data accuracy and monitor changes in financial patterns over time [12].

The Feature Engineering Service operates to extract domain-specific financial indicators from stored data after it has been saved to the system. The system stores these indicators as separate entities which include liquidity ratios debt-to-income levels savings trends and expenditure volatility for future analytical work [8]. AI-based advisory modules use engineered features to deliver personalized financial guidance which they develop without accessing raw transactional data [2]. The system achieves improved accuracy through its separate processes for data capture and feature computation and advisory generation which also enable independent module operation and future explainable machine learning model integration without altering the main data processing system [7].

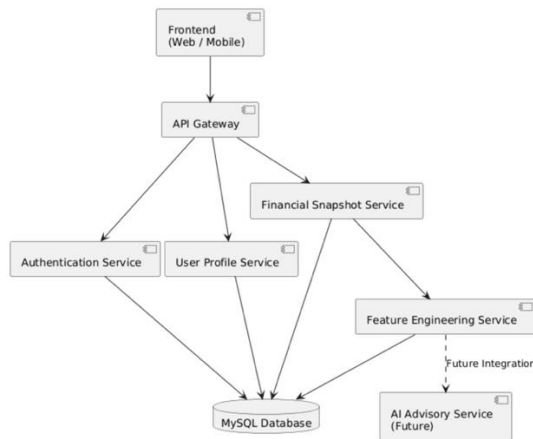


Fig 1: Architecture Diagram

Dataset and Log Preparation

The finance intelligence platform uses a microservices architectural design which operates all its main functions through separate independent services. The system design permits developers to build modules which can scale and maintainability while system components work and develop their functions. The system uses RESTful APIs to handle service communication which enables secure data transfer throughout all platform components. The system uses four microservices which comprise the Authentication Service User Profile Service Financial Snapshot Service and Financial Feature Engineering Service. Each service performs a specialized task which includes user identity verification and profile management and financial data capture and indicator computation.

Number of Records	Features	Target Variable
30000	16	1(yes/no)

Table1: Dataset Overview

The system architecture currently supports existing services while it enables upcoming microservices to be added which include a Credit Scoring Service an Artificial Intelligence Advisory Recommendation Service and a Document Analysis Service. The system pipeline can integrate these services because the architecture framework permits system modules to function independently from existing components. The separation enables developers to create new features which use developed financial indicators for AI-based advisory systems without needing access to complete financial records.

The organization uses a relational database management system to maintain consistent financial records while applying data normalization techniques and protecting data integrity throughout its records. The database schema establishes organized links between user entities and their financial snapshots and the financial indicators which are derived from those snapshots. Users have multiple financial snapshots which document their financial situations at different times so they can keep historical records without needing to delete their earlier saved data. The system maintains traceability and consistency through relational mappings which connect user profiles and advisory outputs and financial documents and computed financial features.

Financial Feature Engineering

The Financial Feature Engineering Service processes raw snapshot data to generate domain-specific financial indicators required for intelligent analysis. The derived features of the system present expense ratio, savings rate, debt-to-income ratio, net worth estimation, and liquidity ratio. The system transforms transactional and financial data into structured analytical variables which improve machine learning modules' ability to understand the data. The feature generation process operates independently from AI inference systems which lets explainable AI to be used in financial advisory recommendations, thereby building user trust while making decisions more understandable.

- The financial snapshot model serves as the primary feature of the system which enables users to view their financial status at specific points throughout the day. The system stores financial snapshots which show users their financial status at different points in time instead of keeping their financial information updated at all times. The system stores historical records of financial snapshots to assist in long-term

research and urgent financial consulting work. The model allows users to discover their financial spending patterns while providing dynamic recommendation systems which adjust according to changes in economic circumstances

- The platform uses multiple security systems to protect its confidential information. The system protects user credentials through password hashing techniques which prevent unauthorized access to secure accounts. The system uses JSON Web Token (JWT) verification to handle its authentication and authorization processes. All system interactions occur through secure API endpoints which maintain controlled access to financial resources. The architecture enables future administrative functions and role-based access control (RBAC) systems which will be used to manage organizational permissions
- Demographic Variables: This includes age(18-65 yrs), regions(urban or rural) and employment type(salarized, self-employed or informal sector).

- Models used for the calculations are:

1) *Logistic Regression:*

$$P(Y=1|X)=1/(1+e^{-(+X)})$$

2) *XGBoost:* Regularized objective function:

$$l = (y,y)^+(fk)$$

- Formulas Used:

$$DTI = TotalMonthlyDebt/MonthlyIncome$$

$$LiquidityRatio = LiquidAssets/MonthlyExpenses$$

$$SavingsRate = (Income-Expenses)/Income$$

$$CreditUtilization = CreditUsed/CreditLimit$$

Experimental Validation

The proposed system was experimentally validated in a controlled laboratory environment using synthetic financial datasets. The test cases were used to validate system functions which tested data movements between microservices and confirmed correct financial indicator calculations and secure access control measures. The validation procedures reached their validation goals because the system now functions at Technology Readiness Level 4 (TRL-4) which shows its practical use in a simulated operational environment.

The following table shows the performance of different models on our dataset

Results and discussion

The performance assessment of the financial snapshot model and its associated feature indicators was executed after the proposed microservices-based finance intelligence system achieved successful functional validation in a laboratory testing environment. The experimental setup required synthetically created financial datasets which replicated actual income patterns and expenditure distributions and asset accumulation trends and liability changes that occurred over time across different user profiles.

The testing phase included access enforcement mechanism evaluation to confirm secure API communication and JWT-based authentication under various simulated user scenarios. The system provided dependable access control together with secure data management which validated the authenticity of financial records and advisory outputs that were stored. The results confirm that the system can produce structured financial intelligence while it establishes a system foundation which will enable future integration of explainable AI-based advisory modules.

Different models performance with our dataset

The logistic regression proved to be the best fit for our project as in theory. XGBoost performed best with real world issues and data.

The reasons that happened are listed below:

- Handles non-linearity
- Robust to feature interactions
- Class imbalance in logistic regression

Model	ROC-AUC	KS Statistic
Logistic Regression	0.96	0.61
Decision Tree	0.89	0.49
Random Forest	0.96	0.60
Gradient Boosting	0.97	0.63
XGBoost	0.95	0.58
SVM	0.95	0.57

Table 2: Performance classification

The figure below shows the comparison between all the trained models by ROC curve.

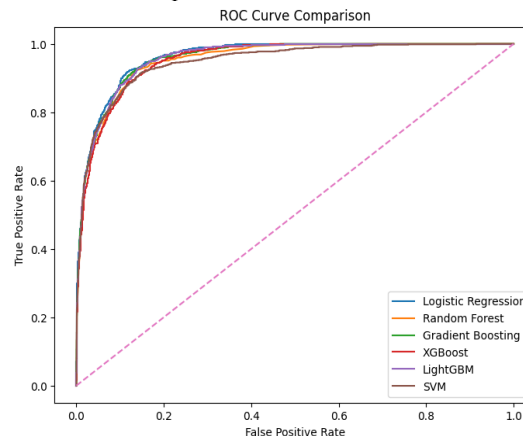


Fig 1: ROC Curve for all models

The experimental results demonstrate that using the feature-first design approach results in better system interpretability and system maintainability. The proposed system architecture achieves two goals by separating financial feature extraction from AI decision-making which results in decreased dependency on hidden predictive models and allows for clear financial assessment. The system offers organizations a flexible solution which enables them to adopt upcoming machine learning methods while maintaining their existing financial data processing system.

Comparison based on statistics

This provides an insight to choose which model in the project based on mean and standard deviation from the pool of central tendencies.

The below provided table shows us that the gradient boosting is the best possible model for us as the deviation is very much less as compared to other models including the ensemble models also.

Model	Mean AUC	Std. Deviation
Logistic Regression	0.958	0.006
Random Forest	0.960	0.005
Gradient Boosting	0.967	0.004
XGBoost	0.955	0.006

Table 3: Central Tendencies

Conclusion

The study introduced the concept of an "AI-Based Financial Advisory and Credit Scoring System," which has the capability to integrate the Indian credit ecosystem with "machine learning models," "explainable AI models," "regulatory compliant credit risk models," and "generative-based financial advisory systems." The study utilized a synthetic dataset to simulate the actual scenario of borrowers. Six supervised models were evaluated using stratified 10-fold cross-validation. The ensemble model was better than the other models in terms of discrimination, and the logistic regression model was better than the other models in terms of probability calibration. From the experimental results, several key conclusions can be drawn. First, it is evident that Ensemble Boosting outperforms other techniques in terms of its discriminatory power. Although, if paired with robust FE techniques, Logistic Regression is seen to be a viable alternative. Optimizing the threshold is seen to have a considerable impact, especially when recalls are a key driver in credit portfolios. Calibration validation is also seen to be appropriate for use in IFRS 9 applications. Finally, SHAP-based explanations are seen to have strong economic consistency with the model predictors. Periodic financial snapshots enable advisors to examine how individual customers or small businesses manage their finances throughout extended periods while providing them with customized historical financial advisory services that adjust with changing time factors. The system components which include authentication and snapshot creation and feature calculation can operate independently through REST-based microservices while their development and deployment processes will not affect the overall system performance. The experimental tests which used synthetic datasets proved that the system components could communicate with one another through secure channels while accessing financial indicators, which proved the system's operational capabilities at Technology Readiness Level 4 (TRL-4) testing stage. The platform serves as a technical solution, which establishes an essential framework that enables the integration of explainable AI models which will produce personalized financial recommendations through transparent systems that users can easily comprehend. The proposed system improves structured financial insights, which will lead to better accessibility for users.

Future Work

The system development team will focus their efforts on building advanced machine learning systems that will predict credit risk and provide personalized financial advice based on financial metrics generated by the Feature Engineering Service. Explainable AI techniques will provide better understanding of advisory recommendations because they enable users to see which elements create advisory results. The system will receive additional enhancements through Document Analysis Service implementation which enables automatic financial information extraction from bank statements and invoices while role-based access control features will help administrators monitor system activities. The system will become more reliable and accurate when experts use actual financial data to assess performance through extensive testing. The upcoming research will investigate two areas which include deploying systems through cloud technology and using Internet of Things devices to collect real-time financial data for monitoring purposes and decision-making assistance. The system can achieve better customization through two technologies which combine behavioral financial analytics with adaptive recommendation engines because these systems automatically adjust to changes in users' financial situations and objectives.

The system will advance into a full financial decision support platform through these developments which will deliver user-friendly advisory solutions based on explainable systems that can handle large-scale operations.

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