© APR 2026 | IRE Journals | Volume 9 Issue 10 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I10-1716861

AI Based Credit Scoring and Risk Assessment Model for Indian banks

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Abstract- ***Credit risk assessment is a fundamental component of financial decision-making in banking and lending institutions. Traditional credit scoring systems rely primarily on static financial metrics and rule-based evaluation methods, which often lack contextual intelligence and adaptability. This paper presents Credit scoring and risk assessment model, an intelligent credit scoring and risk assessment system developed using Large Language Models (LLMs) integrated with AI- based financial analysis and external financial data retrieval. The proposed system combines user financial inputs with real-time financial data retrieved from Yahoo Finance to generate dynamic and explainable risk evaluations. By leveraging contextual retrieval and AI-driven reasoning, the system enhances transparency, adaptability, and analytical depth compared to conventional approaches. Experimental results demonstrate improved interpretability and real-time responsiveness, making the system suitable for modern fintech applications and decision-support systems.***

Index Terms - Credit scoring, risk assessment, large language models, retrieval-augmented generation, financial analytics, fintech.

I. INTRODUCTION

Credit scoring plays a critical role in determining the eligibility of individuals and businesses for loans, credit cards, and other financial products. Financial institutions rely on credit scores to evaluate the likelihood of repayment and assess associated risks. In India, systems such as CIBIL scores are widely used to quantify creditworthiness based on past financial behavior.

However, traditional credit scoring systems have several limitations. They primarily rely on historical data and predefined scoring rules. These systems often lack the ability to incorporate contextual market conditions, real-time financial trends, and qualitative reasoning. Additionally, they provide limited explanation regarding how a final risk score is derived.

With the emergence of Artificial Intelligence (AI) and Large Language Models (LLMs), there is an opportunity to develop more adaptive and intelligent credit risk assessment systems. LLMs are capable of understanding financial narratives, interpreting structured and unstructured data, and generating human-readable explanations.

This paper proposes Credit Scoring and Risk Assessment Model, a novel credit scoring system that integrates Retrieval-Augmented Generation (RAG) with LLMs and real-time financial data from Yahoo Finance. The system aims to improve interpretability, contextual reasoning, and adaptability in credit risk evaluation.

II. LITERATURE REVIEW

Traditional credit scoring models have reckoned on statistical ways similar as logistic retrogression and discriminant analysis. These models use fiscal attributes similar as income, debt- to- income rate, prepayment history, and credit application to cipher threat scores.

Machine literacy approaches similar as decision trees, arbitrary timbers, and support vector machines have bettered vaticination delicacy. These models can identify complex patterns in fiscal datasets but frequently warrant interpretability.

Deep literacy models have also been applied to credit threat vaticination. While they offer high prophetic

performance, they bear large datasets and are frequently considered black- box systems.
Recent advancements in Large Language Models have enabled contextual logic and explanation generation. Retrieval- Augmented Generation(RAG) enhances LLM performance by reacquiring applicable external knowledge before generating responses. still, limited exploration has concentrated on combining RAG and real- time fiscal APIs for credit scoring.

The proposed system addresses this gap by integrating structured fiscal criteria , real- time request data, and AI- driven logic

III. SYSTEM METHODOLOGY

A. System Overview

The proposed system follows a modular architecture consisting of:

- User Input Module
- Financial Data Retrieval Module
- Knowledge Retrieval (RAG) Module
- LLM Processing Module
- Risk Scoring and Explanation Module

The system collects financial inputs from users, retrieves relevant financial and market data, processes the combined information using an LLM, and generates a structured risk assessment report.

B. Data Collection and Processing

The system collects the following user inputs:

- Monthly income
- Existing loan amount
- Credit utilization ratio

Additionally, real-time financial data such as market indices, company financial ratios, and economic indicators are retrieved from Yahoo Finance APIs.
The data is preprocessed and converted into structured prompts for LLM processing.

C. Retrieval-Augmented Generation (RAG)

The RAG architecture enhances the reasoning capabilities of the LLM by retrieving relevant financial knowledge before response generation.
The steps include:

- Retrieving relevant financial data from external financial APIs and datasets.
- Processing the retrieved financial information and combining it with the user's financial inputs such as income, debt, and repayment behavior.
- Creating a contextual prompt that includes both the user financial data and the retrieved financial information.
- Providing the enriched prompt to the Large Language Model for analysis.
- The model then generates a contextual credit risk assessment based on both the retrieved financial information and the user's financial profile.

D. Credit Risk Calculation Model

1. Debt-to-Income Ratio

DTI = Total Monthly Debt / Monthly Income

Purpose:
Measures how much of the user's income goes toward debt repayment

2. Credit Utilization Ratio

CU = Credit Used / Total Credit Limit Purpose:
Indicates the percentage of credit currently used

3. Risk Classification

Low Risk $\rightarrow F \geq 0.75$ Medium Risk $\rightarrow 0.50 \leq F < 0.75$ High Risk $\rightarrow F < 0.50$

E. Large Language Model Integration

- The LLM is responsible for:
- Interpreting financial ratios.
- Analyzing risk indicators.
- Generating structured risk explanations.

Assigning a qualitative risk category (Low, Medium, High).

- The output includes:
- Risk score estimation
- Risk category
- Explanation of contributing factors
- Suggested financial improvements

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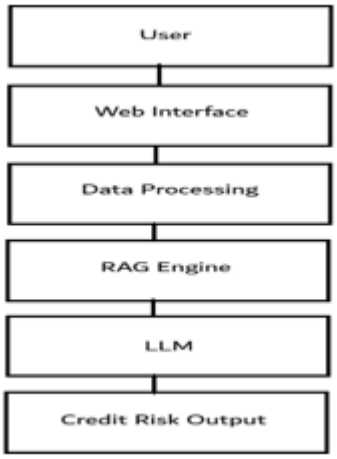

Fig.1. System Architecture of the proposed AI-based credit scoring system

AI-based Credit Scoring and Risk Assessment System represents the overall operation of system architecture. When a user provides financial information via an internet- based interface, the AI system collects certain information such as income, current debts, history of payments and other indicators of financial ability. The information collected through this internet interface will then be processed in the Data Preprocessing Module.

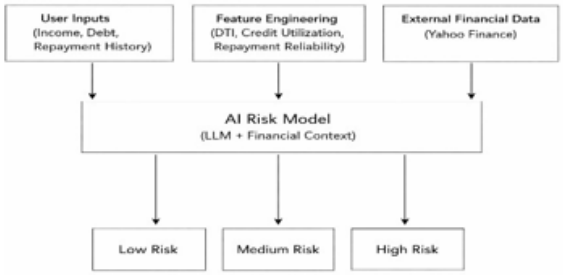

Fig. 2. Credit Risk Data Flow

The Data Preprocessing Module will create features from input data and apply them to the user. Features include such things as debt-to-income ratio, utilization ratio and payment reliability. These indicators are critical to understanding a user's financial behavior.

While processing user data, external financial data will be retrieved from Yahoo Finance through the Yahoo Finance API. This financial market data and economic indicator data from Yahoo provides value as an external source for evaluating credit risk.

The processed user data and external financial data will be stored in a database using an embedding scheme for efficient retrieval of related financial context.

The Retrieval-Augmented Generational Engine (RAG) is a retrieval engine that finds relevant financial knowledge based on the user's financial profile. Additional information about the context is merged with the user's financial input before being used together.

After the enriched data has been combined it's run through a Large Language Model (LLM) which analyzes the financial indicators, interprets risk factor issues, and generates a complete credit risk assessment.

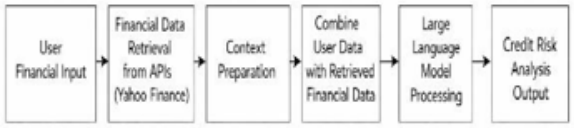

Fig.3. RAG pipeline

The Retrieval-Augmented Generation pipeline augments the reasoning ability of Large Language Models by using external knowledge in the process of producing answers the user receives (answer creation).

The input from the user's question or financial input data is converted to an mapped to embedding representations known as embeddings.Once the user input has been submitted to the system, the retriever searches for and retrieves a set of relevant financial information based upon similarity search of the embeddings of the items found in the database.

The retrieved financial context will be combined with the user's question and passed along to the Large Language Model generator.The LLM will use both the original user input as well as the retrieved financial context to create the most appropriate answer for the user based upon factual context. This allows for increased reliability and accuracy of the

credit risk analysis.The return value produced by the LLM will include the complete structured financial risk assessment (credit risk level, explanation of the financial factors that influenced its creation, etc.

IV. RESULTS

The proposed AI-based credit scoring and risk assessment system was evaluated using multiple financial profiles representing different economic conditions and borrowing behaviors. The objective of the evaluation was to analyze how effectively the system interprets financial inputs and generates contextual risk assessments.

The system processes user financial data such as income level, existing debts, repayment history, and credit utilization. These inputs are analyzed along with external financial data retrieved from financial APIs. The Large Language Model interprets these financial indicators and generates a structured risk evaluation.

To demonstrate the effectiveness of the system, several simulated financial scenarios were tested. Each scenario represented different levels of financial stability and borrowing capacity

A. Case Study Analysis

Case 1: Low Risk Financial Profile

In this scenario, the user has a stable monthly income, low debt obligations, and a consistent repayment history. The debt-to-income ratio remains within a safe threshold, and credit utilization is relatively low.

When the system processes this financial profile, the AI model identifies the user as financially stable. The generated result categorizes the user under the low risk category. The system also provides an explanation indicating that the strong repayment behavior and low credit utilization contribute to the positive risk evaluation.

This result demonstrates that the system can accurately identify financially responsible borrowers.

Case 2: Medium Risk Financial Profile

In the second scenario, the user has moderate income but higher debt commitments. Although the repayment history is generally acceptable, the credit utilization ratio is relatively high.

The system processes these indicators and detects potential financial stress. As a result, the AI model categorizes the user under the medium risk category.

The generated explanation highlights that the elevated credit utilization and increased financial obligations increase the risk of repayment difficulties. However, the consistent repayment history prevents the risk from being classified as high.

Case 3: High Risk Financial Profile

In the third scenario, the user has unstable income and significant outstanding debt. The repayment history shows several delays, and the credit utilization ratio exceeds recommended limits.

After analyzing these indicators, the system classifies the user as high risk. The AI model identifies multiple financial risk factors including high debt burden and poor repayment behavior.

The generated explanation clearly indicates that these financial conditions significantly increase the probability of loan default.

A. Comparative Analysis

The performance of the proposed system can be compared with traditional rule-based credit scoring systems.

Traditional systems typically rely on predefined numerical thresholds and fixed scoring models.
In contrast, the proposed AI-based system provides contextual reasoning and dynamic interpretation.

Parameter	Traditional Credit Scoring	Proposed AI-Based System
Static rule- based evaluation	Yes	No
Contextual reasoning	Limited	High

Real-time financial data integration	No	Yes
Explainability	Low	High
Adaptability	Low	High

The results show that the proposed system provides more comprehensive risk analysis by combining financial indicators with AI-driven interpretation
Observations

The experimental results highlight several important observations:

1. The AI-based model successfully interprets complex financial relationships between income, debt, and repayment behavior.
2. The system provides detailed explanations for credit risk classification, which improves transparency.
3. The integration of external financial data enhances the contextual understanding of financial risk.
4. The model adapts well to different financial scenarios without relying solely on rigid scoring rules.

These observations demonstrate that the proposed system can serve as an effective decision-support tool for credit risk evaluation.

V. CONCLUSION

This paper presented an AI-based credit scoring and risk assessment system designed to improve the accuracy and interpretability of credit risk evaluation. Traditional credit scoring systems rely heavily on static numerical models that often fail to capture the complexity of real-world financial conditions.

The proposed system integrates financial input analysis with artificial intelligence techniques to generate contextual credit risk evaluations. By analyzing financial indicators such as income, debt obligations, repayment behavior, and credit utilization, the system provides a more comprehensive understanding of an individual's financial stability.

The use of Large Language Models enables the system to interpret financial data and generate meaningful explanations for credit risk classifications. This approach enhances transparency and allows users to understand the factors influencing their credit evaluation.

Experimental results demonstrate that the system can effectively categorize users into different risk levels while providing detailed reasoning for each decision. The proposed architecture also supports integration with external financial data sources, enabling dynamic and adaptable credit analysis.

Overall, the developed system provides a promising approach for modern credit risk assessment by combining financial analytics with artificial intelligence. The model can assist financial institutions and lending platforms in making more informed credit decisions while improving the interpretability of risk evaluations.

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