AI-Powered Financial Analysis and Advisory Platform

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Abstract : Small and medium enterprises (SMEs) often maintain financial records but lack access to tools that transform raw data into meaningful insights. This paper presents FinInsight AI, a web based platform designed to evaluate financial health and generate advisory insights from uploaded financial files. The system accepts CSV, XLSX, and PDF documents, processes heterogeneous financial data, and produces a structured analysis that includes a financial health score, risk classification, and advisory recommendations. The architecture integrates a React-based frontend, a FastAPI backend, a SQLite database, and a transparent scoring engine. The system also incorporates an AI-assisted advisory module that generates explanatory insights based on financial metrics. Experimental evaluation using sample SME datasets demonstrates that the proposed approach can effectively differentiate between financially stable and distressed scenarios while maintaining transparency in the scoring process. The platform simplifies financial analysis by presenting results through visual dashboards and concise reports. This approach helps SME owners understand their financial condition, identify potential risks, and make informed decisions for sustainable growth.

***IndexTerms* - SMEs, Financial Health Scoring, Decision Support System, Artificial Intelligence, Financial Data Analysis, WebBased Platform.**

I. INTRODUCTION

Small and medium enterprises play a significant role in economic development by generating employment opportunities and supporting regional business ecosystems. Despite their importance, many SMEs continue to rely on fragmented financial records that are often stored in spreadsheets or basic accounting tools. While such records capture operational data such as revenue, expenses, and cash flow, they rarely provide clear insights into the overall financial health of the organization. In many cases, business owners must manually interpret financial data or depend on external advisors to understand their financial position. This process can be time-consuming and may delay important strategic decisions. The increasing availability of artificial intelligence and data analytics technologies presents an opportunity to address this challenge by transforming raw financial data into actionable insights. Recent studies have explored the application of machine learning, explainable AI, and decision-support systems for financial analytics. These approaches demonstrate the potential of automated systems to assist businesses in interpreting financial data and identifying risk patterns. However, many existing solutions are designed for large enterprises or specialized financial institutions, making them less accessible to smaller organizations. To address this gap, this research introduces FinInsight AI, a lightweight web-based platform that performs automated financial analysis and provides interpretable insights for SMEs. The system enables users to upload financial files, analyze key metrics, and obtain advisory recommendations in a structured and understandableformat.

II.RELATED WORK

Recent research in financial analytics and decision support systems has explored the use of artificial intelligence to improve business intelligence and financial risk assessment. One area of focus involves the application of machine learning techniques for predicting financial distress and credit risk. These models analyze historical financial data to identify patterns associated with business performance and potential financial instability. Another research direction emphasizes explainable artificial intelligence (XAI) in financial decision systems. Traditional machine learning models often function as black boxes, making it difficult for users to understand how predictions are generated. Techniques such as LIME and SHAP have been introduced to provide interpretable explanations of model behavior, allowing users to understand the influence of different financial variables. Recent developments in large language models (LLMs) have also expanded the capabilities of financial analysis systems. These models can generate descriptive explanations of financial metrics and provide contextual insights that assist users in understanding complex financial information. Although these advancements have improved financial analytics, many existing systems remain specialized for tasks such as credit scoring or sentiment analysis. Few solutions provide an integrated platform capable of processing commonly used financial documents and generating comprehensive insights for small businesses. The proposed platform aims to address this limitation by combining financial scoring, explainable analytics, and advisory guidance within a single accessible application.

III.PROPOSEDWORK

The proposed system introduces an integrated financial analysis platform that combines machine learning techniques with explainable analytics to provide interpretable financial insights. The methodology consists of several stages including data collection, preprocessing, model training, interpretability analysis, and evaluation.

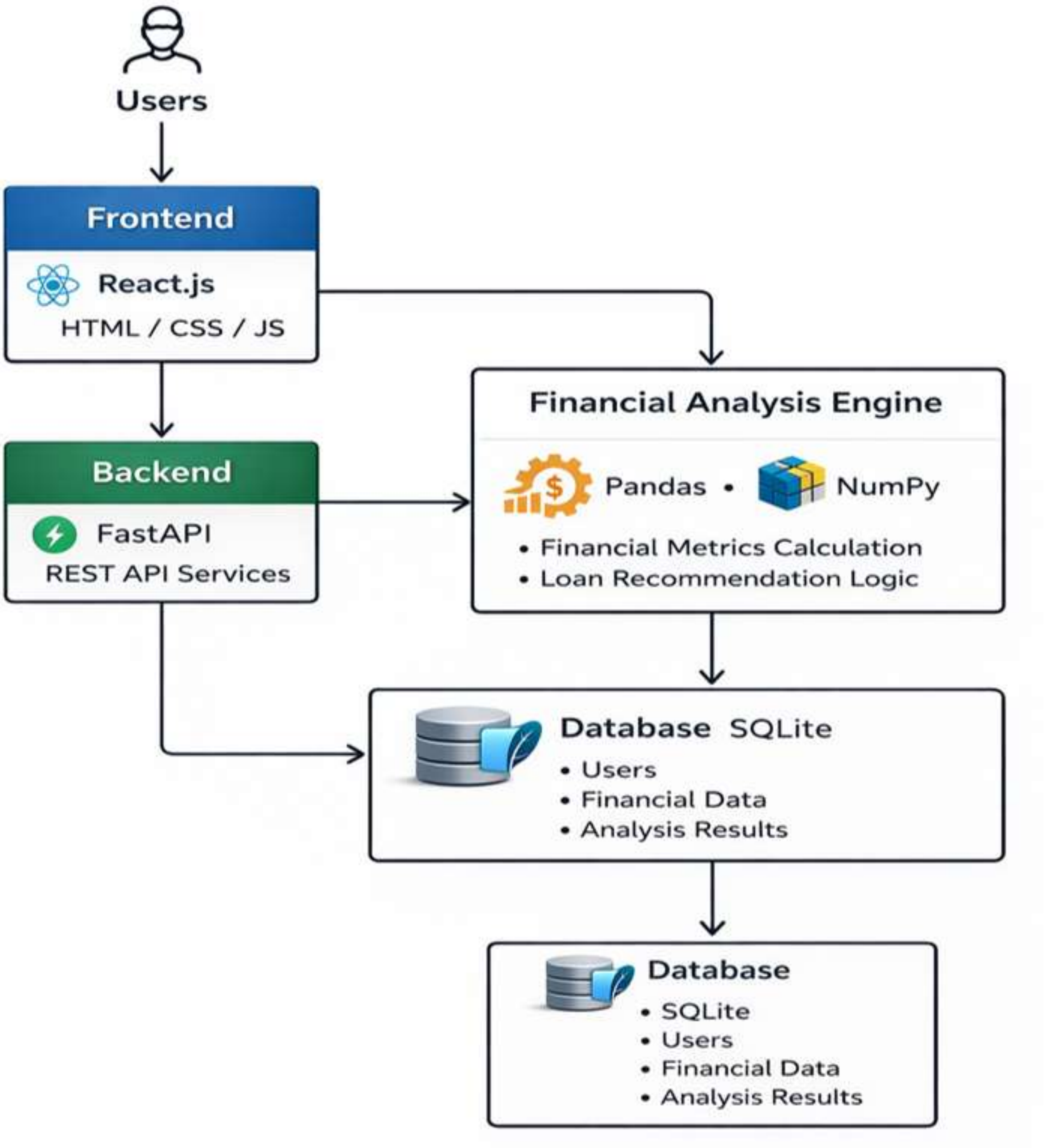

FIG. 1. Proposed Flowchart

A. Data Collection The study utilizes the Lending Club loan dataset, which contains detailed records of loan applications and financial attributes. The dataset includes approximately 10,000 observations across multiple financial variables, such as employment length, loan grade, loan amount, and borrower income. These attributes provide valuable information for modeling financial risk and business performance. B. Data Preprocessing Before model training, the dataset undergoes several preprocessing steps to ensure data quality and consistency. These steps include cleaning missing values, encoding categorical variables, and scaling numerical attributes. Data visualization techniques are also applied to identify potential outliers and irregular patterns within the dataset. Proper preprocessing improves model reliability and helps ensure that the dataset accurately reflects meaningful financial relationships. C. Machine Learning Algorithms To analyze financial risk and predict financial stability, the system employs several machine learning algorithms including Random Forest, LightGBM, and XGBoost. Random Forest Classifier Random Forest is an ensemble learning method that constructs multiple decision trees and combines their outputs to produce stable predictions. This approach reduces overfitting and improves predictive accuracy. LightGBM Classifier LightGBM is a gradient boosting framework designed for efficiency and scalability. It handles large datasets and highdimensional features effectively while maintaining strong predictive performance. XGBOOST Classifier XGBoost is another widely used gradient boosting algorithm known for its high accuracy and regularization capabilities. It can handle missing values and provides flexible hyperparameter tuning options. Explainable AI Integration To enhance transparency, the system incorporates LIME and SHAP techniques for model interpretability. LIME generates local explanations for individual predictions, while SHAP provides a global understanding of feature importance across the entire dataset. These methods allow users to understand how different financial variables influence model predictions.

IV.DESIGN AND METHODOLOGY

The FinInsight AI platform evaluates financial health using a weighted scoring model based on key financial indicators. The scoring framework considers five major factors:

- Profitability (30%)
- Business Growth (20%)
- Expense Management (20%)
- Cash Flow Stability (15%)
- Debt Management (15%)

These indicators are combined to generate an overall financial health score. Industry-specific benchmarks are defined for sectors such as manufacturing, retail, services, technology, agriculture, and logistics. This approach ensures that financial performance is evaluated relative to the characteristics of each industry. Based on the computed score, businesses are categorized into three risk levels:

- Low Risk: Score ≥ 70
- Medium Risk: Score between 45 and 69.9
- High Risk: Score < 45

The system also includes an advisory module that generates recommendations using either AI-generated insights or rule-based guidance. This ensures that the platform continues to function even when external AI services are unavailable.

V.EXPERIMENTAL RESULTS

The platform implementation combines modern web technologies to support data processing and visualization. The frontend is developed using React, while the backend uses FastAPI to handle API requests and perform data analysis. The system also integrates libraries such as pandas for data processing and Chart.js for visualization. During evaluation, three financial datasets representing different business scenarios were analyzed using the proposed system. The results demonstrate that the platform successfully differentiates between financially stable and high-risk businesses. For example, datasets representing manufacturing and retail sectors produced high financial health scores due to stable revenue and controlled expenses. In contrast, a service-based dataset with low profitability and high operating costs was classified as high risk. These results suggest that the scoring framework can effectively identify financial patterns and provide interpretable insights for business decision-making.

VI. CONCLUSION

This study presented FinInsight AI, an AI-assisted financial health assessment platform designed to support small and medium enterprises in analyzing financial performance. The system integrates data ingestion, preprocessing, financial scoring, risk classification, and advisory insights within a single web-based application. By supporting multiple financial file formats such as CSV, XLSX, and PDF, the platform simplifies the process of analyzing financial data. The integration of explainable AI techniques further improves transparency by allowing users to understand how financial indicators contribute to the final health score. The results demonstrate that the proposed platform can effectively evaluate financial conditions and provide useful insights for SME decision making. Future work will focus on expanding dataset coverage, improving predictive models, and integrating real-time financial data sources to enhance system capabilities.

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