IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

FINANCEMCP: AN INTELLIGENT FINANCIAL ANALYTICS SYSTEM USING MACHINE LEARNING AND LARGE LANGUAGE MODELS

Prajwal V Chandgude
Computer Science & Engineering

Om Kumar Singh
Computer Science & Engineering

Pratibha Jaiswal
Computer Science & Engineering

Prince Singh
Computer Science & Engineering

Prof.Vijayakumari G
Assistant Professor
Department of CSE
SOET, CMR UNIVERSITY

Abstract

The rapid growth of financial markets and the increasing availability of financial data have created a need for intelligent systems capable of analyzing and interpreting financial information efficiently. Traditional financial platforms often provide raw financial data but lack intelligent interpretation and decision-support capabilities. This paper presents FinanceMCP, an AI-driven financial intelligence platform designed to assist users in analyzing stocks, mutual funds, IPOs, and macroeconomic indicators within the Indian financial ecosystem.

The proposed system integrates real-time financial data sources with analytical tools and artificial intelligence techniques to provide actionable insights for investors. The platform combines financial technical analysis algorithms such as Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD) with a machine learning model based on Random Forest Regression to estimate portfolio resilience during financial stress conditions.

In addition, the platform integrates a Large Language Model (LLM), Claude by Anthropic, which generates natural-language explanations for financial indicators and analytical results. The architecture of FinanceMCP follows a modular design consisting of a React-based user interface, FastAPI backend services, integrated financial APIs, and a machine learning module for predictive analytics.

Experimental evaluation shows that combining machine learning models with LLM-based interpretation significantly improves user understanding of financial data and supports more informed investment decisions. The proposed framework demonstrates how artificial intelligence and financial analytics can be integrated to build intelligent financial advisory platforms.

Keywords: Financial Intelligence, Machine Learning, Large Language Models, Claude LLM, FinTech Analytics, Portfolio Risk Prediction, Technical Analysis

I. INTRODUCTION

The financial technology (FinTech) industry has experienced significant growth in recent years, driven by the increasing availability of digital financial data and advancements in artificial intelligence technologies. Modern investors increasingly rely on digital platforms to analyze financial markets, track investments, and make informed financial decisions. However, many existing financial platforms primarily provide raw financial data such as stock prices, trading volumes, and market indicators without offering meaningful interpretation or decision support.

Financial decision-making often involves analyzing multiple variables including stock trends, technical indicators, macroeconomic conditions, and portfolio diversification strategies. Traditional financial dashboards present these indicators but offer limited support for interpreting them, especially for retail investors who may not possess strong financial analysis expertise. As a result, there is growing interest in intelligent systems capable of transforming complex financial data into understandable insights.

Recent developments in artificial intelligence, particularly machine learning and large language models, have created new opportunities for developing intelligent financial advisory systems. Machine learning techniques enable systems to identify patterns in financial datasets and perform predictive analysis, while large language models provide natural language explanations that improve interpretability for users.

In this context, this paper proposes FinanceMCP, an AI-driven financial intelligence platform designed to integrate real-time financial data, technical analysis algorithms, machine learning models, and large language models within a unified system. The platform focuses on the Indian financial market and provides features such as stock analysis, mutual fund analytics, IPO tracking, macroeconomic indicator monitoring, and portfolio stability analysis.

FinanceMCP uses technical indicators such as RSI and MACD to analyze market momentum and potential trading signals. A Random Forest Regression model is used to estimate the resilience of an investment portfolio during potential economic stress conditions such as inflation increases or market downturns. To improve interpretability, the system integrates the Claude large language model, which generates human-readable explanations of financial indicators.

The architecture of FinanceMCP follows a modular structure consisting of a React-based frontend interface, FastAPI backend services, integrated financial APIs, and a machine learning module for predictive analytics. This architecture allows the system to efficiently process financial data and deliver analytical insights to users.

The primary contributions of this research are summarized as follows:

Development of an integrated financial intelligence platform that combines real-time financial data with machine learning analytics.

Implementation of a portfolio resilience prediction model using Random Forest Regression for financial stress analysis.

Integration of a Large Language Model (Claude) to generate human-readable explanations of financial indicators.

Design of a modular architecture supporting scalable financial analytics and AI-assisted advisory services.

The remainder of this paper is organized as follows. Section II reviews related work in financial analytics and AI-based advisory systems. Section III describes the proposed system architecture and methodology. Section IV presents implementation details. Section V discusses results and evaluation. Finally, Section VI concludes the paper and outlines potential future work.

II. LITERATURE REVIEW

Financial analytics and intelligent advisory systems have become important research areas in financial technology. With the expansion of digital financial services and financial datasets, researchers have explored machine learning and artificial intelligence techniques to improve investment decision support systems.S

Several studies have investigated the use of machine learning algorithms for financial prediction and risk assessment [1], [2]. Traditional statistical models such as linear regression and time series forecasting have been widely applied to analyze stock market data. However, these models often struggle to capture nonlinear relationships present in financial markets. To address these limitations, algorithms such as Decision Trees, Random Forests, Support Vector Machines, and Neural Networks have been applied to financial datasets [1], [4].

Technical analysis methods are also widely used for financial market evaluation. Indicators such as Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD) help identify market momentum and potential trend reversals [3]. These indicators analyze historical price patterns and assist traders in detecting possible buy or sell signals.

In recent years, AI-driven financial advisory systems have gained attention. These systems combine financial data analytics with automated recommendation engines to generate investment insights. However, many existing systems primarily focus on numerical predictions without providing clear explanations of the underlying financial indicators.

The emergence of Large Language Models (LLMs) has improved the ability of AI systems to interpret structured data and produce natural language explanations. Models such as GPT and Claude demonstrate strong reasoning capabilities and can explain complex information when combined with external tools and data sources [6], [7].

Recent research also explores tool-augmented AI systems, where LLMs are integrated with APIs, databases, and analytical tools to improve reasoning capabilities [8]. Such architectures are particularly useful in financial applications where real-time data and accurate calculations are essential.

Despite these advancements, many existing financial platforms still lack systems that integrate real-time financial data, machine learning-based risk prediction, technical analysis indicators, and LLM-based explanations within a unified framework. FinanceMCP addresses this gap by combining financial analytics, machine learning, and LLM-based interpretation in a single modular system.

III. METHODOLOGY

The proposed FinanceMCP system is designed as an AI-driven financial intelligence platform that integrates financial data acquisition, technical analysis, machine learning prediction, and large language model interpretation.

3.1 System Architecture

The architecture of FinanceMCP consists of four main layers:

• User Interface Layer

• Backend Processing Layer

• Financial Data Integration Layer

• Machine Learning and AI Reasoning Layer

The User Interface Layer provides a web-based dashboard that allows users to search for stocks, analyze mutual funds, monitor IPO listings, and evaluate portfolios.

The Backend Processing Layer, implemented using FastAPI, manages API requests, processes financial data, and coordinates interactions between system modules.

The Financial Data Integration Layer connects the system to external financial data providers such as financial market APIs and macroeconomic datasets [9], [11]. These sources supply real-time information about stock prices, mutual fund NAV values, IPO data, and economic indicators.

The Machine Learning and AI Reasoning Layer contains predictive models and AI explanation modules that analyze financial data and generate insights.

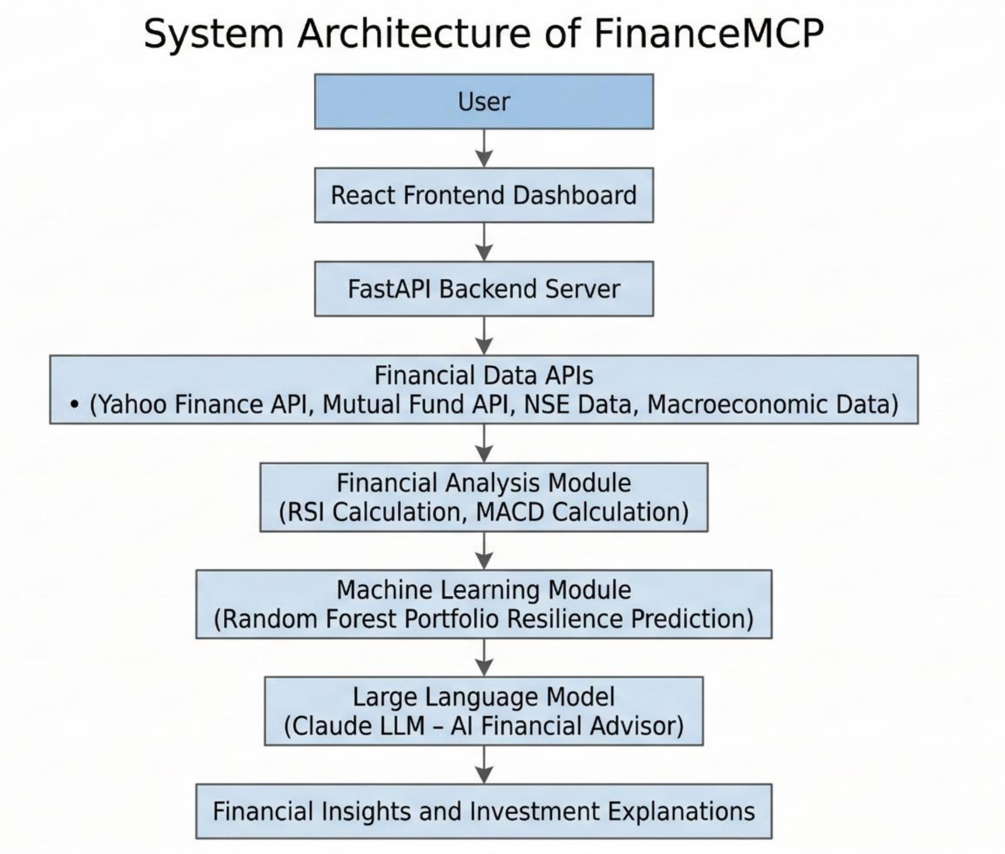

Fig. 3.1: System Architecture of FinanceMCP

3.2 Financial Data Acquisition

FinanceMCP retrieves financial information from multiple publicly available data sources including financial market APIs and economic datasets [9], [11], [12]. These datasets provide stock price data, trading volumes, mutual fund information, and macroeconomic indicators.
The collected data is processed within the backend to support real-time financial analytics.

3.3 Technical Analysis Module

The system calculates key technical indicators commonly used in financial market analysis.
The Relative Strength Index (RSI) measures the magnitude of recent price changes to identify overbought or oversold market conditions [3].
$RSI = 100 - (100 / (1 + RS))$
The Moving Average Convergence Divergence (MACD) indicator measures the relationship between two exponential moving averages of a stock price.
$MACD = EMA(12) - EMA(26)$

These indicators help detect market momentum and potential trend reversals.

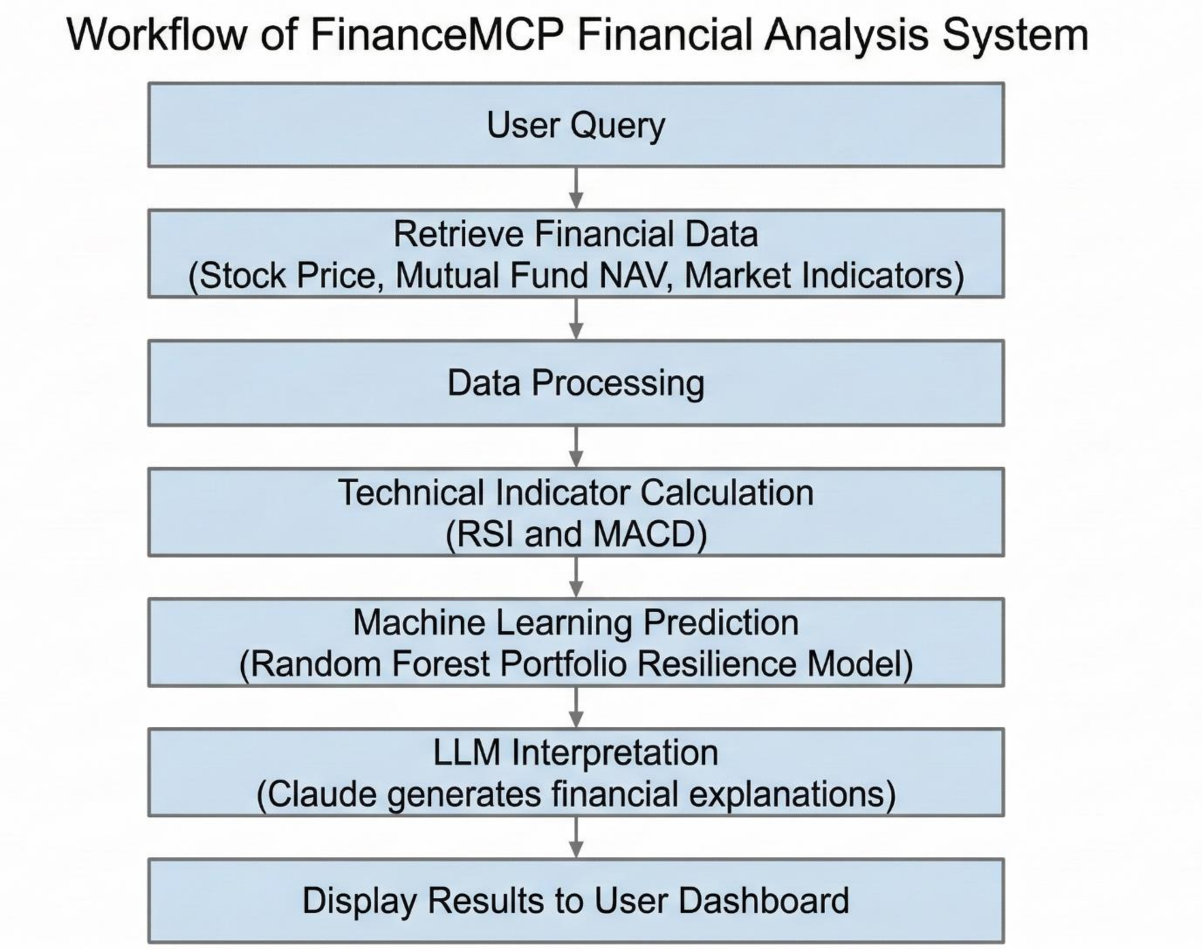

Fig. 3.3: Workflow of FinanceMCP Financial Analysis

3.4 Portfolio Resilience Prediction Model

FinanceMCP includes a machine learning model designed to estimate portfolio resilience under economic stress conditions. The model uses Random Forest Regression, which is effective for financial prediction tasks involving nonlinear relationships [1].

The model analyzes financial parameters such as savings ratio, expense ratio, loan obligations, portfolio volatility, and macroeconomic risk indicators. Based on these inputs, the system produces a resilience score representing the stability of an investment portfolio.

Random Forest models are widely used for predictive analytics because they combine multiple decision trees to improve prediction accuracy and reduce overfitting [1].

3.5 AI-Based Financial Advisor

To improve interpretability, FinanceMCP integrates the Claude Large Language Model developed by Anthropic. Large language models are capable of interpreting structured data and generating natural language explanations for users [6], [7].

When users analyze financial data, calculated indicators such as RSI, MACD, and portfolio metrics are passed to the LLM. The model then generates descriptive explanations describing financial conditions and potential investment implications.

This integration enables the system to bridge the gap between complex financial analytics and user-friendly interpretation.

IV. IMPLEMENTATION

The implementation of FinanceMCP consists of multiple modules responsible for data collection, financial analysis, machine learning prediction, and user interaction.

Step 1: Importing Libraries

Python libraries such as NumPy, Pandas, and Scikit-learn are used for data processing and machine learning. Additional libraries are used for financial API integration and backend processing.

Step 2: Data Acquisition

Financial data is retrieved from external APIs providing stock market information, mutual fund data, and macroeconomic indicators.
Step 3: Data Processing
The retrieved data is cleaned and organized into structured formats suitable for analysis and machine learning processing.
Step 4: Technical Analysis
Technical indicators such as RSI and MACD are calculated using historical price data.
Step 5: Machine Learning Model
A Random Forest Regression model predicts portfolio resilience using financial profile parameters.
Step 6: AI Advisor Integration
The Claude LLM generates explanations and financial insights based on computed indicators and portfolio metrics.
Step 7: Visualization
Results are displayed through a web-based dashboard where users can analyze financial data and view AI-generated insights.

V. RESULTS AND DISCUSSION

FinanceMCP was evaluated using real-time financial data obtained through external financial APIs. The system integrates data retrieval, technical analysis, machine learning prediction, and AI-based explanation within a unified workflow.
The stock analysis module successfully calculated indicators such as RSI and MACD using historical price data. These indicators helped identify potential market momentum shifts. For instance, stocks with RSI values above typical thresholds indicated possible overbought conditions, while lower RSI values suggested oversold conditions.
The machine learning module was evaluated using simulated financial scenarios representing different investor profiles. The Random Forest model analyzed parameters such as savings ratio, expense ratio, portfolio volatility, and macroeconomic risk indicators. The resulting resilience score provided an estimate of the financial stability of the portfolio.
Another key component of the platform is the integration of the Claude large language model. Instead of displaying only numerical indicators, the system provides descriptive explanations of financial metrics. This improves usability by helping users interpret technical indicators and portfolio risk metrics.
The combination of technical analysis, machine learning prediction, and AI-generated explanations enhances the analytical capabilities of the system compared with traditional financial dashboards.

However, the platform relies on external financial APIs for real-time data retrieval, which may introduce latency or temporary data availability limitations in certain scenarios.

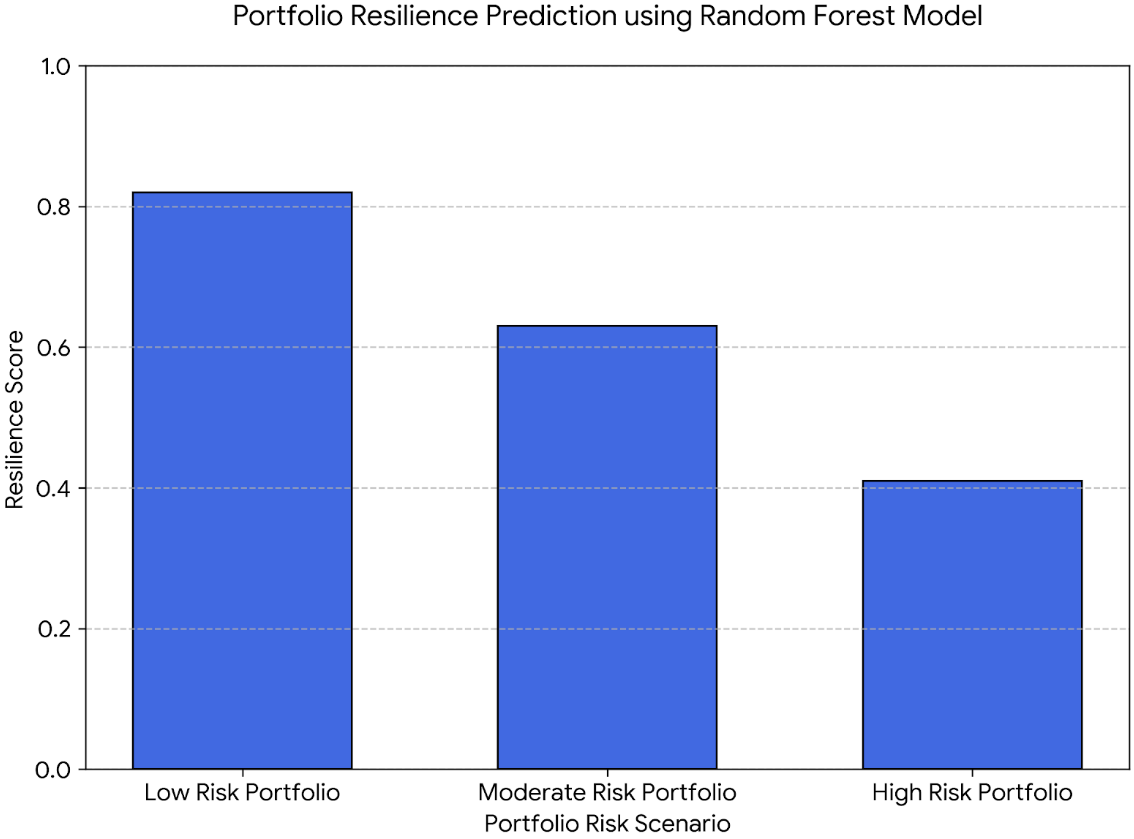

Fig. 5.1: Portfolio Resilience Prediction Results

VI. CONCLUSION

This paper presented FinanceMCP, an AI-driven financial intelligence platform designed to assist users in analyzing financial markets and making informed investment decisions. The system integrates real-time financial data, technical analysis algorithms, machine learning prediction models, and a large language model to provide comprehensive financial insights.

Technical indicators such as RSI and MACD support market trend analysis, while the Random Forest model estimates portfolio resilience under potential economic stress conditions. The integration of a large language model improves interpretability by generating natural language explanations of financial analytics.

The results demonstrate that combining financial analytics with artificial intelligence techniques can significantly improve the accessibility and interpretability of financial information. FinanceMCP provides a practical framework for developing intelligent financial advisory systems.

VII. FUTURE WORK

Future improvements to FinanceMCP may include integrating additional machine learning techniques such as gradient boosting models or neural networks to enhance predictive performance. Incorporating sentiment analysis of financial news and social media data could also improve market analysis by capturing investor sentiment.

Further development may include automated portfolio optimization features that recommend investment strategies based on user risk tolerance. Expanding the platform to support global financial markets and additional financial datasets would also increase the system's scalability and applicability.

REFERENCES

[1] L. Breiman, "Random Forests," Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.

[2] J. B. Heaton, N. G. Polson, and J. H. Witte, "Deep Learning in Finance," Annual Review of Financial Economics, vol. 11, pp. 245–270, 2019.

[3] J. Welles Wilder Jr., New Concepts in Technical Trading Systems, Trend Research, 1978.

[4] T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," in Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2016.

[5] M. Fischer and C. Krauss, "Deep Learning with Long Short-Term Memory Networks for Financial Market Predictions," European Journal of Operational Research, vol. 270, no. 2, pp. 654–669, 2018.

[6] T. Brown et al., "Language Models are Few-Shot Learners," in Advances in Neural Information Processing Systems (NeurIPS), 2020.

[7] Anthropic, “Claude Large Language Model Documentation,” Anthropic AI Research, 2024. Available: https://www.anthropic.com
[8] S. Russell and P. Norvig, Artificial Intelligence: A Modern Approach, 4th ed., Pearson, 2021.
[9] Yahoo Finance API, “Financial Market Data API,” Available: https://finance.yahoo.com
[10] MFAPI, “Indian Mutual Fund Data API,” Available: https://www.mfapi.in
[11] World Bank, “World Development Indicators Dataset,” Available: https://data.worldbank.org
[12] NSE India, “National Stock Exchange Market Data,” Available: https://www.nseindia.com
[13] Kaggle, “Stock Market Dataset for Financial Analysis,” Available: https://www.kaggle.com/datasets
[14] F. Chollet, Deep Learning with Python, Manning Publications, 2018.
[15] J. Devlin, M. Chang, K. Lee, and K. Toutanova, “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding,” in Proceedings of NAACL-HLT, 2019.