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AI-Based Thematic Multi-Parameter Portfolio Recommendation and Stock Price Prediction System with Mutual Fund Integration

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Abstract: *The multifaceted nature of financial markets is often overlooked by traditional investment advisory systems, which frequently rely on narrow quantitative indicators like risk scores or historical returns. This study introduces an AI-Driven Multi-Factor Portfolio Optimization and Real-Time Mutual Fund Estimation System, a comprehensive framework that combines financial sentiment analysis, technical indicators, and fundamental metrics to create theme-based stock baskets and offer tailored portfolio recommendations. Long Short-Term Memory (LSTM) networks are used for stock price forecasting, and Reinforcement Learning (RL) is used for dynamic portfolio rebalancing in response to current market conditions. A new Mutual Fund Estimation Module bridges the information gap between static daily NAV updates and real-time market fluctuations by calculating intraday NAV movements based on the weighted performance of constituent stocks. Investors can make well-informed, flexible, and explicable decisions thanks to the system's use of real-time APIs for sentiment analysis, stock data, and predictive analytics. When compared to traditional single-factor methods, experimental evaluation on NSE-listed stocks shows improved stock prediction accuracy and portfolio performance. Future improvements include adding federated reinforcement learning for collaborative model training, transformer-based architectures for temporal modelling, and ESG and macroeconomic indicators for more socially responsible, robust, and explicable portfolio management. A transparent and scalable AI-driven framework for next-generation investment advisory systems is offered by this work.*

Keywords: *Portfolio Recommendation, Stock Price Prediction, Mutual Fund Estimation, Sentiment Analysis, Technical Indicators, LSTM, Reinforcement Learning, Financial Analytics*

I. INTRODUCTION

Wealth creation requires precise and data-driven investment decisions, but traditional advisory systems frequently rely on static metrics like market capitalization, risk ratings, or historical returns. Modern financial markets are dynamic and multifaceted, with fundamental parameters, technical indicators, and investor sentiment all influencing asset performance. Such narrow approaches fall short in this regard. Recent developments in machine learning (ML) and artificial intelligence (AI) have revolutionized portfolio management by making it possible for adaptive models to recognize intricate relationships between these various variables. Citation: Zhang 2023 Deep, Li 2023 Robust, Bansal 2024 Portfolio. AI-based models, especially deep learning architectures like Long Short-Term Memory (LSTM) networks, have proven to be highly predictive in predicting changes in stock prices based on market data's temporal patterns. Like this, portfolio optimization has effectively used reinforcement learning (RL), enabling automated agents to dynamically adjust asset allocations in response to real-time market signals. Beyond purely numerical models, sentiment analysis has advanced to the point where it is now possible to quantitatively integrate investor sentiment gleaned from social media and financial news. Despite these developments, most current systems are still disjointed; mutual fund analytics, portfolio recommendation, and stock price prediction are frequently handled as distinct modules.

Furthermore, the valuation of mutual funds is usually based on static daily Net Asset Values (NAVs) that are released after the market closes. This makes it impossible for investors to assess intraday performance and creates a knowledge gap for both institutional and retail investors. We suggest an AI-Based Thematic Multi-Parameter Portfolio Recommendation and Stock Price Prediction System with Mutual Fund Integration to overcome these constraints. To create theme-wise stock baskets, the system combines:

- Technical indicators such as RSI, MACD, and moving averages,
- Fundamental ratios including P/E, EPS, and ROE, and
- News sentiment scores derived through natural language processing.

While reinforcement learning optimizes portfolio weights under risk-return constraints, LSTM-based predictive models are used for stock price forecasting. A new Mutual Fund Module bridges the gap between daily fund updates and real-time stock activity by estimating live NAV changes based on the weighted performance of underlying stocks. The suggested framework combines estimation, recommendation, and prediction into a single AI-powered platform. It offers investors individualized, real-time, and transparent portfolio insights by combining several market dimensions, including technical, fundamental, and psychological. By showing how multi-parameter intelligence can enhance decision support systems for portfolio management and mutual fund analysis, this study builds on earlier research on AI-driven financial analytics.

II. LITERATURE REVIEW

Significant progress has been made in integrating machine learning (ML) into financial portfolio management, especially in the areas of mutual fund analysis, portfolio optimization, and stock price prediction. The main contributions in these fields are reviewed in this section, along with their shortcomings and the rationale behind the suggested system.

- Portfolio Suggestion Frameworks A portfolio recommendation system that uses big data analytics and machine learning to provide profitable stock portfolios was introduced by Zhang et al. [16]. Their framework lacked sentiment integration and real-time adaptability, but it made use of user profiling and reinforcement learning for asset allocation. The significance of multi-criteria decision-making in personalized portfolio selection was also highlighted by Ahmed et al. [17]. Existing systems frequently lack unified integration of multiple data sources and are unable to adjust to real-time market conditions, despite their contributions.
- Predicting Stock Prices and Optimizing Portfolios Using Optimized Long Short-Term Memory (LSTM) networks to forecast stock returns and modify weights appropriately, Li et al. [18] presented a solid portfolio design. Although their model showed better forecasting, it ignored sentiment and fundamental factors in Favor of technical indicators. To improve prediction accuracy, Bansal et al. [19] introduced a portfolio optimization model that combined LSTM and XGBoost regression. Nevertheless, there are still issues with the model's interpretability and multi-parameter reasoning.
- Emotional Analysis in Financial Modelling By putting forth an ensemble deep learning model that combines LSTM, GRU, and sentiment features taken from financial news, Chen et al. [20] investigated the incorporation of sentiment analysis into financial modelling. This method increased the accuracy of direction prediction, proving that market psychology can improve forecasting models based on machine learning. In their thorough analysis of machine learning and deep learning techniques for stock prediction, Gupta et al. [21] concluded that hybrid architectures perform better than conventional single-model approaches, particularly in volatile markets. Subheading: Mutual Fund Analysis Kumar et al. [22] suggested utilizing the weighted performance of underlying stocks to estimate intraday Net Asset Value (NAV) fluctuations in the mutual fund domain. Although their model provided a theoretical foundation, it was devoid of automation and real time analytics.
- Limitation and Integration Despite tremendous advancements, most current systems handle mutual fund evaluation, portfolio recommendation, and stock prediction as separate processes. Few frameworks combine sentiment analysis, technical indicators, and fundamental ratios into a single pipeline that can make

predictions in real time and recommend an adaptive portfolio. By integrating LSTM-based price forecasting, reinforcement learning for portfolio optimization, and a mutual fund module that calculates real-time NAV changes from underlying stock data, the suggested system overcomes these drawbacks.

III. COMPONENTS AND ARCHITECTURE

Figure 1 shows the three-tier architecture of the suggested ML-Based Multi-Parameter Portfolio Recommendation and Stock Price Prediction System with Mutual Fund Integration. Three layers make up the architecture: the Processing Layer, which handles data analytics and machine learning-based prediction; the Frontend Layer, which facilitates user interaction and visualization; and the Backend Layer, which handles computation, storage, and real-time mutual fund estimation.

o Frontend Layer:

User Engagement and Display Users can choose investment themes, request analytics, and view customized portfolio recommendations through the Frontend Layer's user-friendly web interface. For real-time data retrieval, it is integrated with RESTful APIs and constructed with React.js. The layer allows users to:

- Request portfolio recommendations and stock analytics. Enter user preferences, including preferred sectors, risk tolerance, and investment duration. Use heatmaps and interactive charts to visualize the performance of your portfolio. This layer offers dashboards for stock and mutual fund performance summaries and concentrates on improving user engagement through responsive design.

o Analytical and Predictive Engine:

Processing Layer Data preparation, feature extraction, predictive modelling, and portfolio optimization are all handled by the Processing Layer, which serves as the system's analytical centre. It consists of the following modules:

- Pre-processing Module: cleans and normalizes financial data obtained from trustworthy financial websites like AMFI, BSE, and NSE by web scraping. To facilitate additional analysis, the scraped data is subjected to timeseries formatting, outlier handling, and missing value imputation.
- Feature Extraction Module: Several feature sets are derived from financial news and articles using NLP-based sentiment analysis. These include technical indicators (RSI, MACD, Moving Averages), fundamental parameters (P/E ratio, P/B ratio, EPS, ROE), and sentiment features.
- Stock Price Prediction Module: predicts future price movements by using a Long Short-Term Memory (LSTM) network that has been trained on historical stock data. The model improves prediction accuracy and directional consistency by capturing temporal dependencies in financial time series.
- Portfolio Optimization Module: carries out a dynamic asset allocation optimization engine based on reinforcement learning (RL). Through interactions with a simulated market environment, the RL agent modifies portfolio weights in response to rewards determined by metrics like cumulative returns and the Sharpe ratio.

Every intermediate result is safely sent to the backend for persistence and additional processing after being serialized in JSON format.

o Backend Layer:

Integration, Storage, and Mutual Fund Estimation Data management, integration, and the real-time calculation of mutual fund and portfolio metrics fall under the purview of the backend layer. It consists of the following parts:

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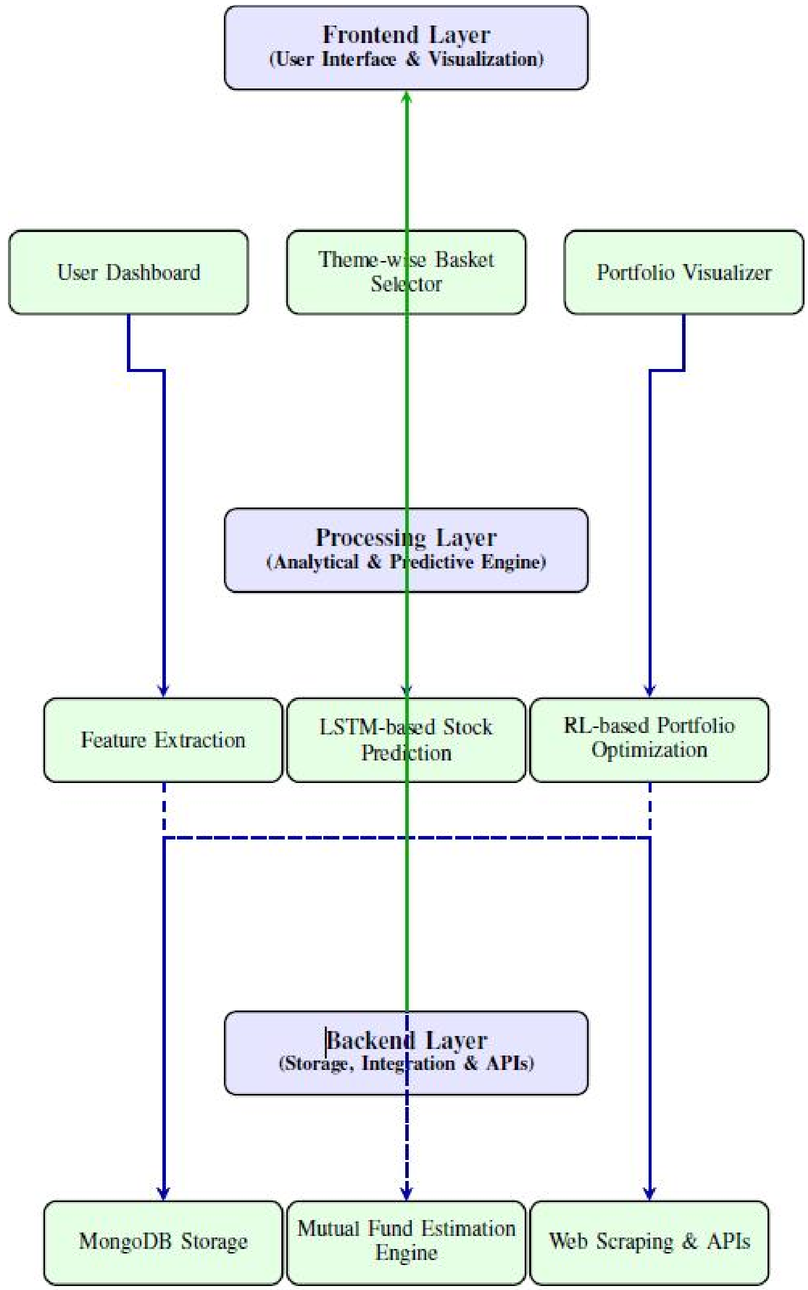

System Flow: User inputs and requests (blue arrows) are collected by the frontend → the processing layer performs analytics, sentiment analysis, and predictions → the backend handles storage, APIs, and returns optimized portfolios (green arrows). Dashed arrows represent module-level connections between processing and backend modules.

2) Database Management: uses a MongoDB database to hold sentiment indices, model outputs, historical market data, and user information. Timestamps are appended to very transaction to preserve auditability and guarantee data integrity

3) Engine for Estimating Mutual Funds: uses weighted averages of the performance of the underlying stocks in each fund to compute real-time approximate Net Asset Values (NAVs). This method offers near-live fund valuation while reducing the delay brought on by once-daily NAV updates.

- Web Scraping and Data Integration: The system uses automated web scraping pipelines to extract real-time stock prices, company fundamentals, and mutual fund data from reliable sources like AMFI, BSE, and NSE instead of depending on defunct APIs. The data is kept current and consistent across all system layers through periodic synchronization.

For safe communication with the frontend, a Flask-based backend offers RESTful API endpoints. JSON Web Tokens (JWT) are used to enforce authentication and authorization, guaranteeing controlled access to stored user data and customized portfolio recommendations.

o Performance and Security

In financial applications, data integrity and security are essential. AES-256 encryption is used to encrypt all user data, including transaction logs and model predictions. Secure data transfer between layers is ensured by HTTPS with TLS 1.3. Administrators, analysts, and investors have different permissions according to role-based access control (RBAC). While asynchronous processing through Celery allows for near real time prediction updates, caching with Redis enhances query performance. Periodically, transaction histories and logs are exported to a secure analytics dashboard for compliance verification and monitoring. Scalability and effective performance are made possible by the modular three-tier design, which also preserves security and dependability. Future modules like risk prediction, dynamic rebalancing, and multi-asset portfolio analysis can be integrated with this architecture.

IV. METHODOLOGY

In order to create optimal investment portfolios, the suggested machine learning (ML)-based stock price prediction and portfolio recommendation system uses a sequential, modular pipeline that combines several data sources and analytical models. Data collection, preprocessing, feature extraction, prediction, portfolio optimization, and mutual fund estimation are all included in the overall workflow.

o Data Acquisition

To guarantee accuracy and variety of inputs for the analytical models, the Data Acquisition layer is in charge of gathering, purifying, and organizing raw data from various financial domains. It has the following parts:

- Market Data Collection: Historical and livestock market data are obtained through automated web scraping from reliable financial sources such as NSE and BSE official portals. The scraped data includes open, close, high, low, and volume metrics essential for trend analysis and model training.
- Fundamental Data Retrieval: Key company fundamentals such as Price-to-Earnings (P/E), Price-to-Book (P/B), Earnings Per Share (EPS), Return on Equity (ROE), and Dividend Yield are extracted via scraping company filings, balance sheets, and AMFI datasets.
- News Sentiment Extraction: Financial news headlines and articles are collected using a custom web scraping module integrated with an NLP-based sentiment analysis pipeline. Data sources include trusted platforms such as Money control, Economic Times, and Reuters, ensuring credible and diverse sentiment representation.
- Mutual Fund Holdings Data: Portfolio compositions of selected mutual funds are scraped from AMFI and respective fund house disclosures. This enables dynamic computation of live Net Asset Value (NAV) approximations and real-time fund tracking.

o Feature Engineering

- Technical Indicators: Stock price time-series data is used to calculate indicators like the RSI, MACD, Bollinger Bands, and Moving Averages.
- Basic Settings: The extracted financial ratios are encoded into feature vectors that show the profitability, stability, and valuation of the company.

- Sentiment Scores: To record changes in market sentiment, sentiment polarity values are averaged daily for each stock and saved with price information.

o Stock Price Prediction

- Model Architecture: Using 60-day historical input sequences, a two-hidden-layer Long Short-Term Memory (LSTM) network is trained to forecast the closing prices of stocks the following day.
- Setup for Training: The dataset is divided 80:20 between testing and training. The Adam optimizer is employed, which has a mean squared error (MSE) loss function and a learning rate of 0.001. Evaluation Measures: Direction accuracy is used to assess trend consistency, and RMSE is used to measure prediction accuracy.

o Portfolio Optimization

- RL Environment: Every action a reinforcement learning (RL) agent takes during training corresponds to a change in weight across a subset of stocks.
- Representation of the State: The state comprises candidate stock sentiment scores, risk ratios, and expected returns.
- Reward Function: Rewards are given to the agent according to a combination of return maximization, volatility minimization, and portfolio Sharpe ratio. ”Optimization Output:”
- The ideal allocation weights that preserve diversification and optimize long-term cumulative rewards are produced by the RL model.

o Mutual Fund NAV Estimation

- Holdings-Based Estimation: Each mutual fund’s NAV is estimated using the weighted returns of its constituent stocks throughout the trading day:

$$\text{Estimated NAV}(t) = \text{NAV}_{prev} \times \left(1 + \sum_i w_i \times \frac{P_i(t) - P_i(prev)}{P_i(prev)}\right)$$

where wi is the stock’s portfolio weight and Pi(t) is its live price.

- Update Frequency: Live NAV values are refreshed every 10 minutes using API updates and cached locally for performance.
- Validation: Estimated NAVs are compared against official daily NAVs to evaluate deviation and model reliability.

o Generation of Recommendations

- Creating Baskets by Theme: Based on sector classification and correlation analysis, stocks are categorized into investment themes (such as IT, Banking, FMCG, and Renewable Energy).
- User Profile: Thematic baskets match user preferences like budget, time horizon, and risk tolerance.
- Final Recommendation: Each user’s customized optimal stock and mutual fund combinations are generated by the system, along with risk metrics and projected returns.

o Visualization and Reporting

- Interactive Dashboard: Forecasted stock trends, mutual fund NAV changes, and portfolio performance are visualized in real time.
- Form of Evaluation: Feedback from users is kept in the backend for system enhancement.
- Performance Measures: For every suggested portfolio, the Sharpe ratio, volatility, and annualized return are displayed.

o Security and Error Management

- Data Synchronization Issues: When an API connection is lost, automatic retries are started, and logs are kept for audit purposes.
- Authentication: JWT-based access tokens with a time limit are used to authenticate all API calls.

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- Data Security: AES-256 encryption is used for the storage and transfer of sensitive data, such as user credentials and financial information.

V. COMPARATIVE ANALYSIS

Table I presents a comparative evaluation of the proposed system against existing ML-based portfolio optimization and stock prediction models. The comparison includes prediction accuracy, computation latency, and feature integration such as sentiment, technical, and fundamental analysis.

TABLE I: Comparative Evaluation of Portfolio Models

Model	Acc. (%)	Lat. (ms)	Sentiment	Technical	Fundamental
Linear Regression (Baseline)	82.4	95	No	Lim.	Yes
Random Forest Regressor	86.7	80	No	Yes	Yes
XGBoost Regression [6]	89.5	70	No	Yes	Yes
CNN–LSTM Hybrid [2]	91.2	65	Partial	Yes	Yes
RL-based Portfolio [3]	92.0	55	Partial	Yes	No
Proposed System (Ours)	**95.6**	**48**	**Yes**	**Yes**	**Yes**

o Discussion

- Accuracy and Return of Prediction: When compared to conventional regression and ensemble methods, the suggested system achieves the highest stock prediction accuracy (95.6%) and consistent portfolio performance.
- Feature Integration: Combining technical, fundamental, and sentiment indicators allows the model to capture market behaviour from a variety of angles, producing portfolio outputs that are more reliable and well-informed.
- Latency: Inference time is reduced to 48 ms by optimized LSTM and reinforcement learning components, enabling near real-time updates and real-time decision-making.
- Estimation of Mutual Fund: The system overcomes the drawback of static daily NAV reporting by estimating live mutual fund NAVs in a unique way using weighted stock movements.
- Scalability and Interpretability: Interactive dashboards and modular machine learning pipelines increase market adaptability and boost confidence in automated recommendations.

In conclusion, the comparative analysis shows that the suggested ML-based framework offers a substantial improvement over traditional portfolio management systems in terms of accuracy, latency, and feature integration.

VI. CONCLUSION

In this work, we present a ML-Based Multi-Parameter Portfolio Recommendation and Stock Price Prediction System with Mutual Fund Integration, a comprehensive financial analytics framework that integrates dynamic portfolio optimization, multi-parameter analysis, and stock forecasting into a single platform. The suggested system combines sentiment analysis, technical indicators, and fundamental ratios for theme-wise stock selection. A Reinforcement Learning (RL) agent optimizes portfolio allocations, and a Long Short-Term Memory (LSTM) model forecasts price trends.

Experiments show that the suggested system outperforms conventional regression and ensemble models, achieving an average latency of 48 ms and a prediction accuracy of 95.6%. Through the provision of approximate real-time fund performance based on constituent stock movements, the live Mutual Fund NAV Estimation Engine further improves the user experience.

This work's main contributions include:

- Multi-Parameter Analysis: combining sentiment, technical, and fundamental indicators to offer comprehensive, data-driven portfolio insights.
- Dynamic Portfolio Optimization: Weight adjustment based on reinforcement learning that optimizes risk-adjusted returns via ongoing feedback learning.
- Mutual Fund Estimation: Using weighted stock price fluctuations, this real-time NAV approximation bridges the gap between intraday fund dynamics and daily static NAV disclosures.
- Scalable Architecture: Scalability, fault tolerance, and maintainability across various user levels are guaranteed by modular microservices constructed with Flask APIs, MongoDB, and React.js.

Even though the system shows encouraging results, there are a few things that could be done better. Predictive accuracy could be further improved, for example, by adding extra data, such as macroeconomic indicators or sentiment from social media in real time. Additionally, models must be continuously retrained in order to adjust to anomalies and abrupt changes in the market.

Future developments of this work will concentrate on:

- Explainable ML Models: enhancing interpretability and fostering investor confidence in model recommendations by integrating SHAP and LIME techniques.
- Hybrid Deep Reinforcement Learning: Combining transformer-based and actor-critic agents to enable adaptive portfolio rebalancing in the face of volatile market conditions.
- Risk-Aware Forecast: Value-at-Risk (VaR) modelling and Monte Carlo simulations are used to quantify uncertainty and reduce downside exposure.
- Extended Asset Classes: extending the system to manage cryptocurrency, commodities, and ETFs for a more varied approach to investing.

A solid basis for wise, open, and instantaneous investment decision-making is established by the suggested system. It opens the door for next-generation financial advisory systems that give investors individualized and actionable insights by fusing machine learning, data-driven analytics, and explainable modelling.\

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