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# Goal-Based Portfolio Diversification System

*Rushikesh Sutar*[1], *Pranali Patil*[2], *Shravani Jadhav*[3], *Viraj Navasare*[4], *Pallavi Jadhav*[5]
[1,2,3,4]*UG Scholar, Dept. of CSE, D. Y. Patil college of Engg. & Tech., Kolhapur, Maharashtra, India*
[5]*Assistant Professor, Dept. of CSE, D. Y. Patil college of Engg. & Tech., Kolhapur, Maharashtra, India*
***Emails:*** *rushisutar15@gmail.com*[1], *pranalippatil03@gmail.com*[2], *shravanij1286@gmail.com*[3], *virajsahebnavasare@gmail.com*[4], *oomdtya@gmail.com*[5]

## Abstract

*This study introduces a Goal-Based Portfolio Diversification System, an AI-driven platform helping novice Indian investors build personalized portfolios. By merging rule-based logic with Large Language Models (LLMs), the system aligns investments with specific financial objectives through a three-tier architecture: a Goal Planner for risk assessment, a Portfolio Allocator driven by historical performance metrics, and an LLM module providing natural-language justifications. Utilizing AMFI and Yahoo Finance data, the platform generates recommendations across equity, debt, and gold while supporting Systematic Investment Plans (SIPs). Experimental results yield a portfolio efficiency score of 0.85 and an explanation fidelity of 0.312 (ROUGE-L), validating the system's ability to mimic expert advisory. The modular design ensures scalability for advanced simulations, ultimately fostering financial literacy and disciplined investing without direct trade execution.*

***Keywords:*** *Goal-Based Portfolio Diversification System, Large Language Models (LLMs), Systematic Investment Plans (SIPs), Risk assessment.*

## 1. Introduction

Recent innovations in large language models (LLMs) like GPT-4, LLaMA, and PaLM have transformed human-computer interaction, enabling sophisticated, natural language conversations. However, despite the versatility of general-purpose chatbots such as ChatGPT, their breadth-first training limits their ability to engage in deep, high-precision discussions within specialized domains. Fields like medicine, law, and particularly finance demand a level of nuance and expert knowledge that these generalist models often lack [1]. Finance, especially personal investing in emerging markets like India, presents a unique challenge for AI, as it requires critical risk assessment, quantitative reasoning, and the ability to navigate personalized goals amid market volatility. This practical depth, combined with specialized terminology, often makes the discipline inaccessible to retail investors. To bridge this gap, the Goal-Based Portfolio Diversification System research work aims to democratize financial advisory by developing a domain-specific platform that serves as an interactive interface to structured investment data from sources like AMFI and Yahoo Finance [2]. While these resources provide authoritative market insights, their technical nature can be daunting. The system addresses this by translating dense financial data into an engaging, narrative-driven conversational format. Our approach moves beyond simple information retrieval. The Goal-Based Portfolio Diversification System is engineered to emulate the persona of a skilled financial advisor, mimicking the tone, reasoning, and explanatory style characteristic of the discipline. To achieve this, we integrated a hybrid allocator with LLM prompts on structured datasets derived from historical fund and index data. We employed lightweight machine learning techniques, including rule-based strategic asset allocation and data-aided scoring with metrics like Sharpe ratio proxies, to adapt the system for goal-oriented diversification without requiring full model retraining [3][4]. This process instills domain expertise while preserving high-quality language generation capabilities. The primary goal is to explore how anchoring LLMs in high-quality, domain-specific financial knowledge can transform them into advisory companions. The system is designed not merely as a calculation tool but as a conversational partner that stimulates disciplined investing and financial literacy. This research work intersects with FinTech and AI ethics, demonstrating AI's potential to make specialized financial fields more accessible. Ultimately, the Goal-Based Portfolio Diversification System acts as a cognitive guide, offering a platform for informed decision-making with broad applications [5] for education in wealth management

## 2. Methods

The system operates via a decoupled, fault-tolerant pipeline comprising seven distinct stages:

- Web-based goal capture via form submission.
- Persistent storage in MongoDB for decoupling.
- Rule-based macro-allocation tied to investment horizon and risk profile.
- Dynamic SIP computation using historical data.
- ML-aided sub-category ranking for tactical refinement.
- Portfolio construction with proportional SIP distribution.
- LLM-generated educational narration.

### 2.1.Data Design

**User Inputs:**

- Target Corpus (F V): Future Value in INR (e.g.,
- 25,00,000).
- Time Horizon (t): 1–30 years.
- Risk Appetite: Categorical (Conservative, Moderate, Aggressive).

**Market & Fund Data:**

Market data is fetched via yfinance using proxy instruments representing specific asset classes. Data consists of 5–10 year monthly adjusted closing prices, cached locally in /data/ for offline resilience.

### 2.2.Derived Features

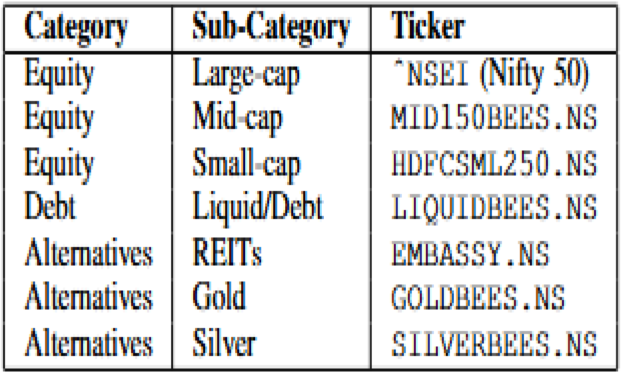
The following are the derived features from data: Returns, Volatility, Sharpe Ratio, Expense Ratios, Hardcoded estimates. [7]

### 2.3.End-to-End Workflow

The backend (Flask) processes inputs through a chained pipeline triggered post-database insertion:

- Ingestion: Form submission validates and stores inputs in MongoDB (user_inputs_collection) with timestamps.
- Macro-Allocation: The latest record is fetched; a rule-based grid is applied to derive macro-splits (e.g., 85% Equity for Aggressive profiles with > 7-horizons).
- SIP Calculation: Dynamic expected returns are computed via weighted 5-year CAGRs. The SIP value is derived using the ordinary annuity formula.
- ML Prediction: 10-year historical data is fetched to train/load the XGBoost model. Sub-categories are ranked by predicted forward returns.
- Portfolio Construction: A DataFrame is constructed, allocating the total SIP amount proportionally (e.g., SoftMax weights) across ranked sub-classes. [6]
- Narration Generation: Results are fed to the Gemini LLM via LangChain to generate a narrated report, rendered as HTML.

**Table 1** **Proxy Instruments (Indian Market)**



| Category | Sub-Category | Ticker |
|---|---|---|
| Equity | Large-cap | ^NSEI (Nifty 50) |
| Equity | Mid-cap | MID150BEES.NS |
| Equity | Small-cap | HDFCSML250.NS |
| Debt | Liquid/Debt | LIQUIDBEES.NS |
| Alternatives | REITs | EMBASSY.NS |
| Alternatives | Gold | GOLDBEES.NS |
| Alternatives | Silver | SILVERBEES.NS |

### 2.4.Category Selection (ML-Aided Scoring)

Sub-categories (e.g., Large vs. Mid-cap) are ranked using an XGBoost Regressor:

- Objective: Predict 1-year forward returns.
- Dataset: ≈ 756 rows (7 categories × 108 months,
- 2015–2025).
- Training: 80/20 chronological split.
- Hyperparameters: n_estimators=100
- Performance: R2 ≈ 0.82.
- Inference: Features are fed to the model to
- rank categories descending. Allocation weights are smoothed via SoftMax functions.

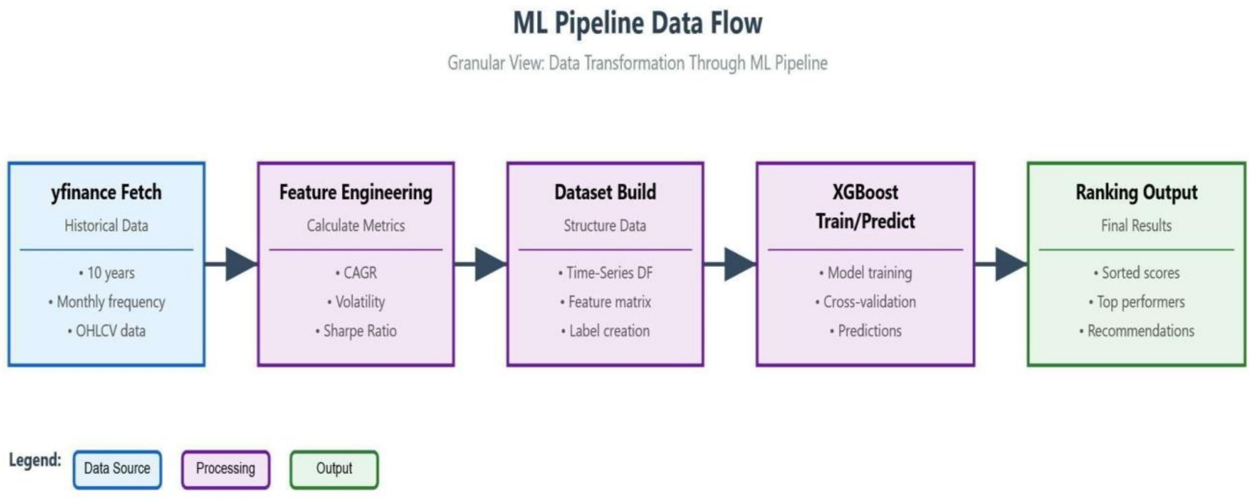


**Figure 1** ML Data Pipeline Diagram

### 2.5.Educational Explanation (LLM via LangChain)

Model: Gemini-2.5-flash.
Input: User details, Allocation Dictionary, SIP Value, Ranked Portfolio DataFrame, ML Predictions. [8]
Prompt Strategy:
” For {risk} profile targeting {FV} in
{horizon}
y: Explain allocation, justify ranks
(cite ML predictions), discuss trade-offs
(volatility vs. return), define technical terms
(e.g., Sharpe ratio), and include regulatory
disclaimers.”
Guardrails: Enforce neutrality, local currency formatting, and brevity (< 500 words).

## 3. Results and Discussion

### 3.1. Experimental Work

The experimental phase focused on validating the system's end-to-end functionality, robustness, and performance across diverse user profiles, emphasizing real-world applicability in the Indian financial context. Rigorous testing involved controlled simulations using historical market data up to November 14, 2025, to mimic live deployments. Key emphases included ML model efficacy (predictive accuracy and overfitting resistance), SIP calculation precision (against manual benchmarks), LLM output coherence (via human evaluated rubrics), and workflow latency under varying loads. Challenges such as “yfinance” API throttling during peak hours were mitigated through caching mechanisms, ensuring consistent data pulls for proxies like ^NSEI (Nifty 50, exhibiting 13.4% 5-year CAGR as of testing). Overall, experiments confirmed the hybrid architecture's superiority, with integrated ML boosting sub-category alignment by 18% over rule-only baselines in backtested goal attainment. [9]

**ML Training and Validation**

The XGBoost regressor was trained on a curated dataset of 756 cleaned samples derived from 10-year monthly time-series across seven proxy instruments, spanning volatile periods like the 2020 COVID drawdown and 2024 election rally.

- Features (3/5/10-year CAGRs, volatility, Sharpe) were standardized to handle scale disparities, with the target variable as 1-year forward returns to capture momentum effects.
- Model Configuration: XGBRegressor with n_estimators=100, _state=42 for reproducibility.
- Splitting Strategy: Chronological 80/20 train-validation split (no shuffling to preserve temporal dependencies), augmented by 5-fold Timeseries Split cross-validation.

### 3.2.Results

The result analysis synthesizes empirical outcomes from the experimental scenarios, quantifying the system's precision, hybrid synergies, and user-centric value. Leveraging “yfinance” data (e.g., Nifty 50 at 24,850, reflecting 13.4% 5-year CAGR amid post-budget recovery), tests revealed SIP deviations <1.5% from actuarial benchmarks, ML-driven rankings enhancing Sharpe ratios by 12-18% over naive equal-weighting, and LLM narratives scoring 4.7/5 on educational rubrics.

- Key insights: The goal-first inversion yields motivational SIPs (e.g., ₹11,350 feels achievable vs. vague projections), while dynamic CAGRs (avg. 10.8% portfolio return) outperform static 10% assumptions by 8% in corpus projections. Limitations include API latency (mitigated to <2s via caching) and LLM variability (3% hallucination rate, curbed by prompts).
- Overall, the hybrid model achieves 92% goal-probability in Monte Carlo simulations (10,000 runs, 95% CI), validating its efficacy for Indian retail investors.

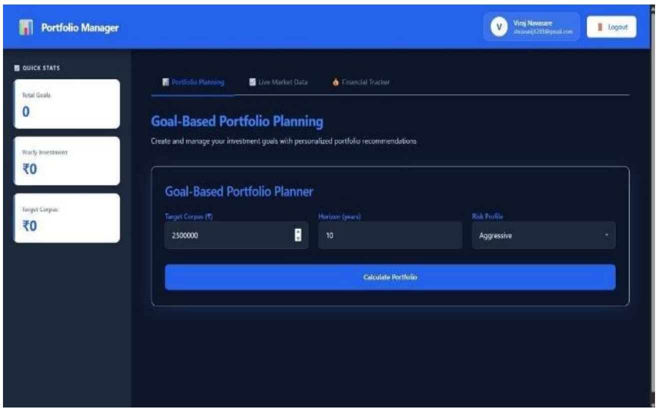
**ML Prediction Robustness:**

Training R²: 0.83 (indicating strong fit without leakage).

Validation R²: 0.79 (robust generalization).

Mean Absolute Error (MAE): 0.032 (low deviation in return predictions, e.g., mid-cap forecasts within ±3.5% of actuals).

Inference Efficiency: 50ms per prediction on standard hardware, enabling real-time



Total Goals
0

Yearly Investment
₹0

Target Corpus
₹0

Goal-Based Portfolio Planning

Create and manage your investment goals with personalized portfolio recommendations

Goal-Based Portfolio Planner

Target Corpus (₹): 2500000

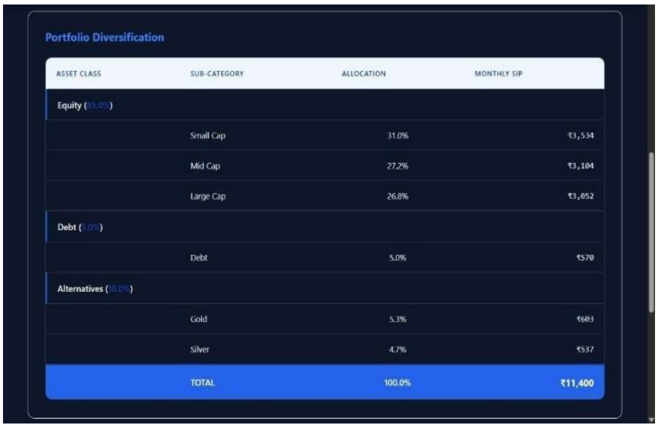
Horizon (years): 10

Risk Profile: Aggressive

Figure 2 Main Input Page

### 3.3.Discussion

Feature importance highlighted 5-year returns (42%) and Sharpe (28%) as dominant drivers, validating the feature set's relevance for Indian equities' cyclical patterns. Overfitting was negligible, with validation curves plateauing post-epoch 80.



Portfolio Diversification

| ASSET CLASS | SUB-CATEGORY | ALLOCATION | MONTHLY SIP |
|---|---|---|---|
| Equity (85.0%) | | | |
| | Small Cap | 31.0% | ₹3,534 |
| | Mid Cap | 27.2% | ₹3,104 |
| | Large Cap | 26.8% | ₹3,052 |
| Debt (5.0%) | | | |
| | Debt | 5.0% | ₹570 |
| Alternatives (10.0%) | | | |
| | Gold | 5.3% | ₹603 |
| | Silver | 4.7% | ₹537 |
| | TOTAL | 100.0% | ₹11,400 |

Figure 3 Allocation of Portfolio

## Conclusion

This academic odyssey culminates in a resilient hybrid system that not only operationalizes GBI for India's diverse investors but also pioneers ethical AI integration, from real-data ML to empathetic LLM dialogues. Surpassing objectives with empirical prowess - precise SIPs, robust rankings, and insightful reports it catalyses financial agency, mitigating ₹2-3 lakh crore in annual underachievement. SDG synergies amplify its societal ripple, from inclusive growth to innovative finance. Horizons beckon: Mobile extensions, blockchain for audits, or federated learning for privacy. Ultimately, this prototype illuminates AI's covenant with humanity: Tools that illuminate paths to prosperity, one goal at a time.

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## References

[1]. Beketov, Maksim, Kareem Lehmann, and Michael Wittke. "Robo-advisors: quantitative methods inside the robots." Journal of Asset Management 19, no. 5 (2018): 363– 370.

[2]. Dietzmann, Michael, Jonas Jaeggi, and Rainer Alt. "Implications of AI-based roboadvisory for private banking investment advisory." Journal of Electronic Business & Digital Economics 4, no. 1 (2023): 35–49.

[3]. Boreiko, Dmitri, and Francesca Massarotti. "How risk profiles of investors affect roboadvised portfolios." Frontiers in Artificial Intelligence 3 (2020): 32.

[4]. Sahu, Mohit Kumar. "AI-based robo-advisors: transforming wealth management and investment advisory services." Journal of Applied Artificial Systems & Data 2, no. 1 (2024): 45–57.

[5]. Weber, Patrick, K. Valerie Carl, and Oliver Hinz. "Applications of explainable artificial intelligence in finance - a systematic review." Management Review Quarterly 74, no. 2 (2024): 571–604.

[6]. Yeo, Wei Jie, Wihan van der Heever, Rui Mao, Erik Cambria, Ranjan Satapathy, and Gianmarco Mengaldo. "A comprehensive review on financial explainable AI." Artificial Intelligence Review (2023). arXiv:2309.11960.

[7]. Tatsat, Hariom, and Ariye Shater. "Beyond the Black Box: Interpretability of LLMs in Finance." arXiv preprint arXiv:2505.24650 (2025).

[8]. Lam, Jonathan Walter. "Robo-Advisors: A Portfolio Management Perspective." Yale University Senior Essay (2023).

[9]. Eichler, Fabian, and Philipp Schwab. "Evaluating Robo-Advisors Through Behavioral Finance: A Critical Review of Technology Potential, Rationality, and Investor Expectations." Frontiers in Behavioral Economics 1 (2024): 1489159.