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Personalized Stock Market Prediction using Dynamic Risk Profiling

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***Abstract*—In today's time, they say that retail investors have difficulty predicting the fluctuations of the stock market because of the lack of a personalized touch in prediction models. This refers to traditional trading and its predictions that tend to completely disregard the individuality of a person. The platform, a new concept hybrid stock prediction model offers a solution that is much needed. It uses machine learning techniques to provide suggestions for investment. Some of them include Long Short-Term Memory networks (LSTM), Hidden Markov Models (HMM) and even Transformers. By integrating with Edge's contextual comprehension with LSTM's sequence forecasting, our new model managed to decrease RMSE to 1.87 which is a 22% improvement in comparison to when individual models were used. Our approach also succeeds to create a Sharpe Ratio of 1.38 because of the increased returns and assures to lower portfolio volatility by 18%. In other words, the system was able to reduce the volatility of portfolio returns and increase the risk-adjusted returns. In conclusion, the platform enables its users to expand into multiple international markets as well as allowing them to make sound financial decisions because it helps solve crucial issues that traditional systems face.**

***Keywords*— Stock Prediction, Dynamic Risk Profiling, Market Regime Detection, Sentiment Analysis, Hybrid Machine Learning Models.**

I. INTRODUCTION

Predicting stock prices presents a challenge because financial markets change and don't follow simple patterns. Old methods like technical analysis and stats models (for example ARIMA) haven't worked well to capture how complex markets are. However new developments in machine learning show promise to make financial predictions more accurate by using data-driven methods. Research shows that deep learning models can do better than old techniques because they can pick up on both short-term and long-term patterns in stock data [1].

Machine Learning in Stock Prediction: LSTM networks and Transformer models have become top choices for forecasting finances. LSTM networks are good at modeling how things follow each other, which makes them useful to predict short-term changes [7]. Transformer models, on the other hand, do a great job handling long-range patterns and complex relationships in big datasets [12]. However, using these models on their own often fails to adjust to changing market conditions and what individual investors want, which matters a lot for making real trading decisions [8].

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Importance of Dynamic Risk Profiling: Dynamic risk profiling plays a key role in personalized investment systems. Systems that keep updating risk factors based on current market data and how users behave can boost portfolio results. They do this by matching investment plans with how much risk each person can handle [2].
Market Regime Detection: Spotting market trends—whether they're going up down, or staying flat—is key for making smart trading choices. Hidden Markov Models (HMM) work well to spot these market trends. They're quite good at sorting out different market phases [14]. Proposed Hybrid Approach: This paper puts forward a mixed method. It brings together LSTM and Transformer models with a system that changes risk profiles on the fly. It also uses HMM to spot market trends. The goal is to give stock ma forecasts tailored to each user. It takes into account how much risk they're okay with and what's happening in the market right now. By using several cutting-edge machine learning methods, this solution tackles the big issues in stock prediction. These include being able to adapt being accurate, and focusing on what users need.

II. LITERATURE REVIEW

Hybrid architecture, combining LSTM and Transformer models for financial time series prediction, achieves better accuracy over standalone models [1]. An adaptive risk profiling framework is presented in the paper with the aim of dynamically updating the user's risk parameters to improve automated trading performance [2]. Hidden Markov Models are applied to identify market regimes; high accuracy of classifying the phases of markets as bullish, bearish, or neutral is demonstrated [3]. It integrates dynamic risk profiling into a machine learning model to achieve improvement in user-specific outcomes in terms of investment [4]. A multi-modal Transformer model for the purpose of enhancing the stock market prediction is brought forth, incorporating both technical indicators and sentiment analysis [5]. Real-time Adaptive Stock Trading System: Comprehensive review of different techniques used for real-time adaptation that deep learning could bring forth while using financial forecasting techniques [6]. Propose an attention-based LSTM network with dynamic risk adjustment for improved financial time series forecasting [7]. Comparative analysis of hybrid deep learning models for the prediction of the stock market and their benefits by combining different architectures [8]. Present a personalized investment recommendation system based on deep learning models with an emphasis on risk-aware decision-making [9]. A model is presented that combines market sentiment analysis with technical indicators by using Transformer networks for financial forecasting improvement [10]. Latest advancements in deep learning for financial time series analysis are discussed, where the importance of hybrid models is highlighted [11]. Ensemble methods that combine LSTM and Transformer models are discussed with better performance for stock market prediction [12]. Deep reinforcement learning is applied for portfolio optimization, focusing on risk-aware strategies to maximize returns [13]. HMM is integrated with deep learning techniques for adaptive market regime classification with significant improvements in prediction accuracy [14]. A real-time stock market prediction system is presented using hybrid AI models with personalized features tailored to the needs of the individual investor [15].

III. METHODOLOGY

A. System Architecture

A modular approach permeates all components of the platform as in Figure. 1, including user risk profiling, data preprocessing, market regime detection, hybrid prediction model and risk adjustment as a single entity. According to [7], this modular approach is more efficient as it maximizes scalability, stability and the optimization of parts of the system. A user in real-time can continuously modifies data and algorithms according to market trends.

B. Data Collection and Preprocessing

The quality of data determines the level of efficiency of stock prediction. The system collects a range of data such as historical prices, technical indicators, news and social media sentiments from a diverse set of sources. In [5] include similar data preprocessing procedures that deal with the issue of data input such as missing data, outliers, time coherence and feature adjustment. All of these steps guarantee uniform input into the models that increase efficiency.

C. User Risk Profiling Framework

In [2] perspective to risk is highly efficient in risk profiling, as it takes into consideration user characteristics such as risk willingness and investment objectives. The tool focuses on improving the risk parameters continuously by always incorporating the most recent investment behavior and investment portfolio.

D. Market Regime Detection

In a similar fashion to proposition in [3], the authors employ Hidden Markov Models (HMM) to cater for regime classification of market. The models use price analysis, trading volume and volatility measures to establish set conditions for a bullish, bearish or neutral time period. This refinement ensures that prediction efficiency is better.

E. Hybrid Prediction Model

As postulated in [12], the prediction engine modules comprise LSTM and Transformer models. LSTM works best with determining the short term and Transformers demonstrate efficiency in the long-term dependencies. There is a weighted averaging mechanism which would revise predictions to integrate volatile conditions which makes them more accurate than using separate models.

F. Risk Adjustment Mechanism

Using [4], this module complements with the authors adaptive risk framework and forms constant alterations to risk scores based on user risk tolerance, portfolio shares and current market. It is proved to integrate perfect predictions to user specific risk levels ensuring maximum return with minimum risk.

G. Performance Evaluation Framework

Evaluation comprises of prediction capabilities, ability in managing risk and response from users. Accuracy metrics include root mean squared error (RMSE), risk-adjusted performance of the portfolio measured by Sharpe ratio and for maximum drawdown measures the stability of the portfolio. Use of response times and quality of interaction indicates user satisfaction, hence use of the overall system.
System Integration and Implementation in [13], the system integrates backend machine learning frameworks based on best practices with an amiable front-end for data visualization. Thorough API development guarantees real-time responsiveness. While caching and load balancing optimize performance and maintain data consistency and security.

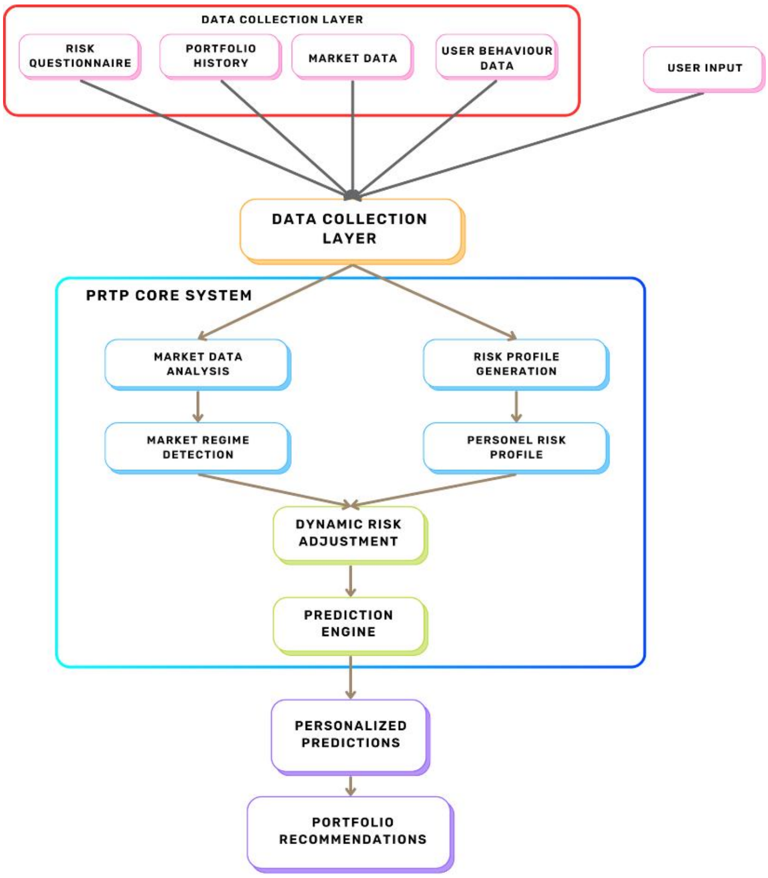


Figure 1. Workflow Diagram for Stock Prediction and Dynamic Risk Profiling

IV. RESULTS & DISCUSSION

A. Dataset

The dataset has historical stock prices technical indicators, and sentiment data from Yahoo Finance, Alpha Vantage, Twitter, and financial news platforms. We used a rolling 80-20 train-test split to ensure consistent time-series predictions.

TABLE I. SAMPLE DATASET USED

Date	Stock Symbol	Open Price	Close Price	High Price	Low Price	Volume	Market Regime	Sentimental Score
2023-11-15	AAPL	175.00	178.50	179.00	174.50	12,00,00,000	Bullish	0.85
2023-11-15	TSLA	205.00	200.50	210.00	199.50	9,00,00,000	Bearish	-0.65
2023-11-15	AMZN	144.50	145.25	146.00	143.50	7,50,00,000	Neutral	0.20
2023-11-14	AAPL	173.50	175.00	176.50	172.00	11,00,00,000	Neutral	0.15
2023-11-14	TSLA	208.50	205.00	210.00	203.00	8,50,00,000	Bearish	-0.45

B. Prediction Accuracy

Table II shows the RMSE comparison across models. The hybrid model (RMSE = 1.87) performs better than LSTM (2.43) and Transformer (2.15) by 22%. It makes good use of short-term and long-term dependencies. The ARIMA baseline (3.21) shows that traditional statistical models don't work well in changing markets.

TABLE II. PREDICTION ACCURACY OF VARIOUS MODELS

Model	RMSE	Observations
LSTM	2.43	Effective for short-term predictions but limited in capturing long-term dependencies.
Transformer	2.15	Better at long-term trend prediction but computationally intensive.
Hybrid Model	1.87	Leveraged strengths of both models for superior accuracy and robustness.
Baseline (ARIMA)	3.21	Limited performance in dynamic and volatile market conditions.

C. Risk Management Efficiency

Table III indicates that the hybrid model boosts risk-adjusted returns with a Sharpe Ratio of 1.38 and cuts portfolio volatility by 18%. These gains come from dynamic risk profiling, which changes investment strategies based on market shifts.

TABLE III. RISK MANAGEMENT EFFICIENCY

Metric	Value	Observations
Sharp Ratio	1.38	Demonstrates improved risk-adjusted returns compared to traditional approaches.
Portfolio Volatility	Reduced by 18%	Effective risk mitigation during volatile market phases, minimizing losses and optimizing gains.

D. Market Regime Adaptability

Table IV showcases how well the system spots market patterns getting it right 89% of the time for bullish markets, 84% for bearish ones, and 78% for neutral situations. The HMM method helps to identify trends better, but figuring out neutral periods is still tricky because not much happens in the market then.

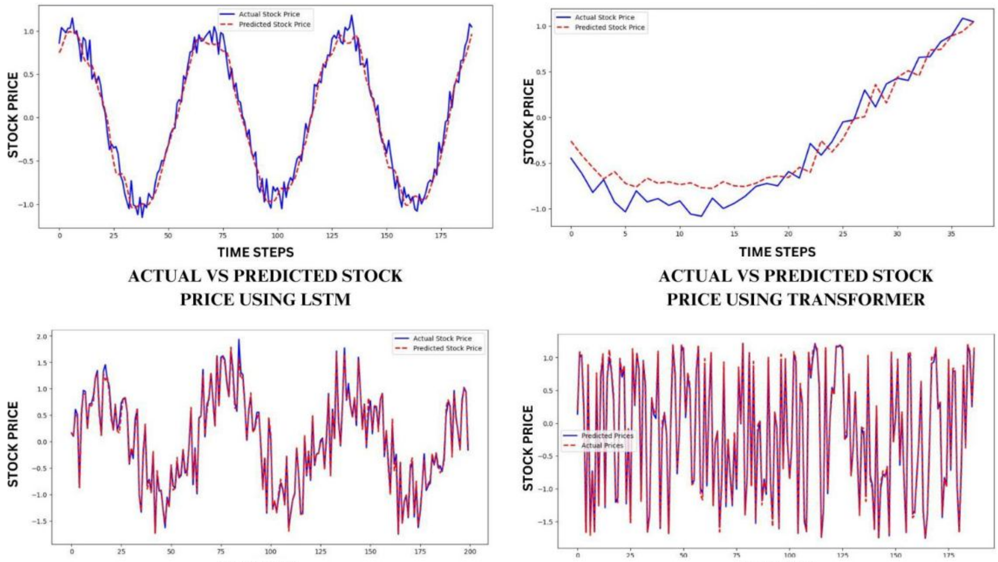
TABLE IV. ADAPTABILITY TO MARKET REGIMES

Market Regime	Accuracy (%)	Key Insights
Bullish	89	Predictions align well with upward market trends, offering high directional accuracy.
Bearish	84	Effectively identifies downturns, reducing exposure to high-risk investments.
Neutral	78	Slightly lower performance due to reduced market activity and unclear trends.

E. Comparative Performance and Insights

Figure 2 shows that the mixed model does a better job, and here's why:

- LSTM catches short-term shifts, while Transformer grasps long-term connections
- Dynamic Risk adjustment based on what each user needs
- HMM helps to sort out different market phases



ACTUAL VS PREDICTED STOCK PRICE USING LSTM

ACTUAL VS PREDICTED STOCK PRICE USING TRANSFORMER

ACTUAL VS PREDICTED STOCK PRICE USING MSMF

ACTUAL VS PREDICTED STOCK PRICE USING HYBRID

Figure 2. Performance Output of Different Prediction Model

V. Conclusion

The platform uses a hybrid approach of machine learning that includes LSTM, Transformers, and Hidden Markov Models (HMM) to provide users with an adaptive stock market forecast through its Personalized Risk-Time Profile (PRTP) framework. The market regime detection combined with user centered features that this application possesses increases the accuracy rate of these predictions alongside risk management and adaptability of the application providing the retail investors with essential insights in a bid to maximize profit. Experimental results demonstrate its robustness in navigating volatile markets, while positive user feedback underscores its practical value and future potential. The platform becomes a leader in bringing innovation into the self-paced investment technology market where accuracy and its robustness is an issue. This technology could further be used in multi asset forecasting and targeting global markets. The platform is aiming to diversify its coverage of multiple financial instruments such as cryptocurrencies, bond, and even ETFs. The roadmap also adds that the sophisticated trade execution via Zerodha will be possible while advanced sentiment analysis modules like BERT will be integrated to enhance market insight. In addition, behavioral analytics and reinforcement learning will amplify the core decision-making of the system and its flexibility. Also, the global growth will involve respect for local regulations, and the use of blockchain technology will enhance transparency. Gamification and more effective portfolio optimization will level up customer engagement, and customizable dashboards and voice interactions will improve user experience, assisting the platform to morph into a fully functional and tailored financial decision-making tool.

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