

Minimax Optimization and Multi-Agent Deep Reinforcement Learning for Intelligent Stock Market Forecasting and Decision-Making

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Abstract

This study presents a comprehensive survey of recent advancements in stock market forecasting frameworks and techniques. Various machine learning, deep learning, deep reinforcement learning (DRL), and hybrid models applied to stock markets across regions such as the United States, China, Europe, and India have been analyzed. The survey identifies critical research gaps and challenges in stock forecasting, including handling diverse stock profiles, managing class imbalance, addressing model drift, and improving predictive accuracy. To address these challenges, a novel three-phase methodology is proposed, incorporating a Multi-Agent Deep Reinforcement Learning (MA-DRL) model. The proposed framework aims to deliver superior forecasting performance, enhance profitability, effectively manage stock volatility, and achieve robust performance under dynamic market conditions.

Keywords: Deep learning Deep reinforcement learning Forecasting High-frequency trading Machine learning Multi-agent Predictive model Stock market Volatile

1. Introduction

The rapid evolution of financial technology has transformed traditional investment landscapes, with predictive analytics emerging as a foundation of this transformation [1]. Among the most challenging and high-stakes applications in financial technology is stock price prediction, where the intricate interplay of market dynamics, socio-economic factors, and global events creates a volatile and unpredictable environment [2]. Events such as the recent economic disruptions caused by the global pandemic underscore the complexity of these challenges, highlighting the urgent need for advanced predictive frameworks capable of adapting to rapidly changing environments [3]. Stock price volatility is influenced by a multitude of interconnected variables, including financial indicators, political developments, societal trends, and global economic shifts. For investors, accurate stock trend prediction is crucial not only for maximizing returns but also for mitigating risks. Moreover, predictive insights directly impact listed companies, influencing their reputation, market valuation, and growth potential. This dual importance for both investors and corporations underscores the critical role of robust stock forecasting methodologies [3].

Despite decades of research, the question of when to buy or sell stocks remains an elusive puzzle. The widely debated Efficient Market Hypothesis (EMH) posits that stock prices reflect all available information, rendering it impossible to consistently outperform the market through predictive analysis [1], [2]. However, the linear models traditionally used to support EMH fail to capture the nonlinear and complex interactions inherent in financial markets. This has led to the exploration of nonparametric machine learning techniques [3], [4] capable of uncovering hidden patterns in vast and intricate datasets, challenging the limitations of EMH and opening new avenues for predictive success [5].

The last decade has witnessed a paradigm shift in stock market analysis, fueled by the advent of machine learning and artificial intelligence (AI) [6]. Neural networks, in particular, have gained prominence due to their ability to model complex nonlinear relationships without relying on predefined parametric structures [6], [7]. These models have proven adept at processing historical and real-time data, enabling more accurate and dynamic predictions [8]. However, the integration of stock price forecasting with actionable trading strategies has emerged as a critical frontier, requiring methodologies that can adapt to the fluid nature of financial markets [9].

Reinforcement learning (RL) [10], with its ability to enable autonomous agents to learn optimal trading strategies through trial-and-error interactions, has shown remarkable potential in this domain. Unlike supervised learning techniques, RL focuses on maximizing long-term rewards through dynamic decision-

making, making it particularly suitable for the complexities of stock trading. Recent advancements have expanded the capabilities of RL by incorporating multi-agent systems, where multiple interacting agents collaborate to optimize outcomes. Building on these advancements, this research proposes a novel stock trading framework that leverages multi-agent systems to enhance the performance of deep reinforcement learning-based models [10]. By addressing critical challenges such as market volatility, class imbalance, and model drift, this framework aims to deliver a robust, adaptive, and scalable solution for stock market prediction and trading. Through this, the study sets the stage for developing next-generation stock management systems capable of handling the complexities of modern financial markets. The research significance is as follows.

The work provides a detailed study of different deep learning models, focused on deep reinforcement and their usage in stock forecasting management. Provides a more detailed study of performance metrics, benchmark used, and limitation of current methods. Highlighted the research gaps of the current methods. The study provides a three-phase model to address the research gaps.

The paper is organized as follows. Section 2 provides different stock market predictive models and identifies the research gaps. Section 3 provides more detailed findings of the work in terms of metrics and dataset with limitation of models. Section 4, the proposed methodology is provided. The last section provides conclusion of the research work with future work is provided.

2. Literature Survey

This section conducts extensive surveys of various existing stock market forecasting and predictive models using deep learning-based methodologies. Y. Li et al. [11], introduced Layered-wise hierarchical-frequency decomposition combined with gated recurrent unit (GRU)-based deep learning for feature extraction with adaptive learning rates. The significance of the model is it enhanced prediction accuracy by addressing multiscale dependencies in financial data. However, the limitation is it involves high computational complexity and limits scalability for real-time applications. Sukono et al. [12] introduced moving average convergence-divergence (MACD)-based K-Means clustering integrated with Mean value at risk (VaR) for portfolio design. The significance is it is effective for balanced portfolio allocation considering market volatility. However, the limitation are its reliance on historical data may not fully capture sudden market shifts. Al-Sheebah and Al-Fuhaidi et al. [13] introduced GRU algorithm incorporating endogenous and exogenous variables. The optimization is done through gradient-based optimization for time-series forecasting. The significance is it improved prediction by considering broader macroeconomic variables. However, the model performance diminishes with incomplete or noisy external data. T. Jayanth et al. [14] introduced “Single Exponential Smoothing with Dual Attention based Bi-directional Long Short-Term Memory (LSTM) optimize with Bayesian Optimization (SES-DA-BiLSTM-BO)” hybrid model for high-frequency data analysis where BO is used for effective hyperparameter tuning. The significance are it achieves superior accuracy in high-frequency financial data predictions. However, the limitation are it is tailored for high-frequency data; less effective for low-frequency datasets.

A. Bâra et al. [15] introduced dynamic analysis of Brent Crude Oil, S&P 500, and Bitcoin prices using econometric modeling with multi-variable regression. The significance is it highlights interdependencies between major economic indicators. However, the limitation is limited to specific asset classes; generalization to broader datasets is unclear. Y. Zhao [16] et al. introduced machine learning algorithms for credit risk assessment, where feature selection and gradient-boosting optimization is done to provides scalable solutions for medium and microenterprise risk evaluation. However, the limitation it only focuses on credit data; limited applicability to direct stock price forecasting. Ansari et al. [17] designed MC-GNN (Multi-Cluster Graph-Neural-Networks) for stock forecasting to captures complex interrelations among financial entities effectively. However, the limitation is the model complexity demands significant computational resources. Mahdi Ashrafzadeh et al. [18] introduced clustering-based return prediction using Particle Swarm Optimization (PSO)-Convolution neural-networks PSO-CNN combined with MVF (mean-variance forecasting), where PSO is used for pre-selection and CNN for feature extraction to boosts portfolio returns. However, the limitation is it requires substantial preprocessing; may lag in volatile markets.

Kojima et al. [19], introduced non-harmonic analysis for periodic component visualization of NASDAQ using time-varying decomposition employing signal processing techniques. The model provides insights into periodic trends for long-term strategy formulation. However, the limitation is it focuses on NASDAQ; applicability to other indices needs validation. Ramezankhani et al. [20] introduced Transudative learning-based early warning system for housing and stock markets using LSTM-based Off-policy optimization for dynamic learning with differential evolution-based hyperparameter optimization. The significance is it is effective for early risk detection in Korean stock and housing markets. However, the limitation is the performance may degrade with high-dimensional or sparse data. Das et al. et al. [21] introduced feature ensemble framework integrating technical analysis with the Aquila Optimizer for feature selection and model training. The significance is it demonstrates improved prediction accuracy by optimizing feature sets for technical indicators. However, the limitation is the dependency on technical indicators that limit applicability in markets influenced by fundamental factors. Martínez-Barbero et al. [22] introduced LSTM for portfolio optimization in European markets employing gradient-based methods. The significance of the model

effectively captures upward and downward market trends for enhanced portfolio returns. However, the limitations are limited generalizability to volatile or highly irregular market conditions.

Bessler et al. [23] introduced Sector-based risk-return prediction models with econometric modeling integrated into portfolio optimization frameworks. The significance is it highlights the value of sector-specific dynamics in improving portfolio efficiency. The limitation is it assumes consistent sectoral performance, which may not hold during economic disruptions. Kabbani et al. [24] introduced deep reinforcement learning (DRL) for automated trading systems. The optimization strategy adopted is policy-gradient-based learning to adapt trading strategies dynamically. The significance is it provides robust automation for trading in volatile stock markets. However, the limitation is the scalability issues for multi-asset trading in diverse market environments. Muhammad et al. [25] introduced explainable deep learning using attention mechanisms for stock trend prediction, where the attention-based feature weighting is used as optimization strategy to enhance model interpretability. The significance is it enables decision-making with insights into model reasoning. However, the model induces higher computational complexity for real-time applications. Li et al. [26] introduced DRL model [27] incorporating multi-modal data fusion for portfolio adaptation to market changes. The significance is it leverages diverse data sources for dynamic portfolio optimization [28]. The limitation is it lack of explainability for the combined impact of fused data sources of Chinese stock market. Zhang et al. [29] introduced reinforcement learning for high-frequency trading under reward-driven learning to optimize trade execution rates. The significance is it is tailored for regulatory compliance while maximizing trading efficiency. However, the model is restricted focus on Chinese markets with T+1 rules. Jeribi et al. [30] introduced expert system integrating deep learning for portfolio prediction and forecasting using multi-objective optimization to balance portfolio risk and return. The significance is it demonstrates flexibility in multi-market portfolio management. However, the limitation is it increased complexity when scaling diverse and large datasets.

This survey underscores the diverse methodologies and optimization strategies leveraged in stock price forecasting and portfolio optimization, highlighting their strengths and limitations. The following are the research gaps that is identified in stock market prediction and forecasting. The current DL and DRL-based stock prediction model exhibit poor accuracy when dataset is imbalanced in nature. Requires huge amount of training data and suffers from model training underfitting and overfitting problem. No prior work has considered employing the multi-agent DRL model for stock prediction and forecasting. How to integrate micro and macro data into stock prediction must be studied. Need to develop a model to identify features contributing to accurate stock prediction model. Identify model drift over time to minimize the loss [31]. In the next section the work provides more depth study of core datasets and limitation of work; thereby more improved stock forecasting management framework can be developed.

3. Findings

Table 1 highlights the methodologies, datasets, performance metrics, and their significance and limitations of different methodologies. The finding in table 1, aids the researcher to develop new techniques, datasets and metrics that can be used for validating stock forecasting models.

Table 1: Comparative study

Author, Ref, Year	Methodology Used	Dataset Used	Performance Metrics	Significance	Limitation
A. K. Das et al. [21], 2024	Feature ensemble framework combining technical analysis and Aquila Optimizer for stock forecasting.	S&P 500 index (technical indicator data).	Accuracy, RMSE.	Robust feature integration with optimization enhances prediction accuracy by 89.9%.	Limited to technical indicators; fundamental data not considered.
Martínez-Barbero et al. [22], 2024	Portfolio optimization using LSTM neural networks on upward/downward trends in European markets.	EURO STOXX 50 and FTSE 100 indices.	Portfolio return, Sharpe ratio.	Captures directional trends effectively for enhanced portfolio management with Up to 12% return improvement in upward markets	Underperformance in volatile markets with irregular patterns.

W. Bessler et al. [23], 2024	Sector return prediction models with portfolio optimization techniques.	Global sector data (sectoral indices).	Return, Risk-adjusted return (Sharpe ratio).	Focus on sectoral dynamics boosts portfolio efficiency with 15% improvement in risk-adjusted returns.	Dependence on sector models limits cross-sector correlation insights.
T. Kabbani et al. [24], 2024	Deep reinforcement learning (DRL) approach for trading automation.	Nasdaq and NYSE historical price data.	Profitability, Trading efficiency, Reward per action.	Effective for dynamic trade execution in volatile markets with profitability improvement by 20%.	Scalability to multiple assets not tested.
D. Muhammad et al. [25], 2024	Explainable deep learning for stock trend prediction using attention-based neural networks.	SSE Composite Index, DJIA.	Prediction accuracy, F1 score.	Improved interpretability aids decision-making with Accuracy: 85%; F1: 0.78.	Complex models require high computational power.
H. Li et al. [26], 2024	DRL model with data fusion techniques for portfolio management.	Market and alternative datasets (news sentiment, social media).	Cumulative returns, Alpha, Sharpe ratio.	Data fusion improves adaptive trading in dynamic markets that outperforms benchmarks by 18%.	Limited explainability of fused data effect.
Yitao Qiu et al. [27], 2024	DRL combined with quantum finance theory for portfolio investment management.	US Stock Market indices and quantum financial data.	Profitability, Risk, Reward metrics.	Innovative integration of quantum theory with DRL that outperform by 22% in tested scenarios.	Practical implementation complexity remains a challenge.
A. Muminov et al. [28]	Bitcoin price direction forecasting using Deep Q-Networks (DQN).	Bitcoin market price dataset (hourly/daily data).	Accuracy, Precision.	Demonstrates high precision in predicting volatile cryptocurrency prices with Accuracy: 92%; Precision: 0.85.	Generalizability to traditional stocks not established.
W. Zhang et al. [29], 2024	Reinforcement learning for T+1 rule-based high-frequency trading.	Chinese Stock Market data (SHSE, SZSE).	Trade profit, Execution rate.	Adapts effectively to T+1 trading constraints in HFT with 18% higher trading profit compared to benchmarks.	Focuses narrowly on Chinese markets and T+1 rules.
F. Jeribi et al. [30], 2024	Expert system framework using deep reinforcement learning for portfolio prediction and forecasting.	Multi-market data (global stocks, forex).	Portfolio risk, Annualized return, Sharpe ratio.	Versatile system capable of multi-market portfolio management with Sharpe ratio improved by 25%.	Complexity increases with multi-market analysis.

4. Proposed Methodology

The proposed methodology is aimed at developing a novel stock market prediction and forecasting framework using novel multi-agent deep reinforcement learning system that achieves higher accuracy considering volatile stocks thereby increasing profit to the end-client. The proposed methodology is implemented in three phases as follows. In phase 1, the work will develop a new deep reinforcement learning algorithm considering both micro and macro data into stock predictive model.

This work first study current machine learning, deep learning, DRL-model, and hybrid models applied for stock market forecasting and prediction. The study shows various deep learning models have been presented for stock market forecasting; however, these models lack in identifying new pattern, as a result the accuracy if forecasting impacted. The study shows two notables baseline model introduced in [29] and [30] employing deep reinforcement learning. However, [29] is tested for Chinese market; on the other side, [30] investigated on different market. However, these work employs single agent to model market behavior with lesser number of features and volatility behavior of market is not modeled effectively. The work introduces a new DRL-based stock market framework by considering both micro-macro data into predictive model. Model performance and comparative study will be done on recent work and benchmarks.

In phase 2, the work further develop a multi-agent system to assess both short and long-term behavior for stock price forecasting. The work introduces novel multi-agent DRL-based stock market framework by identifying features contributing to stock surge and stock volatility. Once multi-agent DRL is developed, the work introduces a model to understand both short-term and long-term market behavior. The work will develop an effective forecasting algorithm employing multi-agent DRL model to optimize the feature weight across different stock market features. Address the class imbalance issue employing robust weight adjustment mechanisms. Validate the forecasting performance in terms of accuracy, RMSE etc. Comparative study with recent stock forecasting methodologies considering stock market datasets.

In phase 3, the work identifies model drift and feature contributing to stock volatility for attaining robust predictive model considering different stock market dataset such as S&P500, and DAX market. The market trends keep changing with respect to time; thus, it is important to identify model drift and factors contributing to stock volatility. The new drift identification combined with MA-DRL will be tested on different stock market data to study the model performance.

5. Conclusion

This work first conducted a survey of recent stock forecasting and predictive framework and techniques have been studied. Here different stock market forecasting model using machine learning, deep learning, DRL, and hybrid model designed on different stock market countries such as US, China, European, and Indian have been studied. The survey identified the challenges through research gap that involved in stock forecasting and prediction management framework considering different stocks profiles. The work introduced a three-phase proposed methodology to model enhanced stock market management framework using novel MA-DRL model. The proposed model is expected to achieve superior forecasting performance, enhance stock profit, identify stock volatility, address class-imbalance issues of predictive model and handle model drift for attaining robust performance. Future work would consider developing the proposed three-phase model and testing different stock market data considering short-term, long-term stock profiles, micro and macro dataset considering highly volatile stocks.

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Mr. Syed Mushtaq Ali	✓	✓	✓		✓	✓		✓	✓	✓	✓		✓	
Dr. Rafeeq Mohammed	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓		

C: Conceptualization

M : Methodology

So : Software

Va : Validation

I : Investigation

R: Resources

D : Data Curation

O : Writing - Original Draft

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

Fo : Formal analysis

E: Writing - Review & Editing

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