Spcm: A Deep Learning Approach For Stock Price Prediction And Investment Portfolio Optimization

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Abstract:

In the rapidly evolving financial landscape, the need for intelligent, data-driven investment strategies has become increasingly crucial. Traditional portfolio management techniques often rely heavily on historical averages and human judgment, which may not effectively adapt to market volatility and complex economic variables. This project, titled "Portfolio Optimization Using Deep Learning," aims to develop a robust and predictive framework for asset allocation using advanced Deep Learning techniques. The core of this system leverages Long Short-Term Memory (LSTM) networks, a specialized type of recurrent neural network (RNN), capable of learning long-term dependencies and trends from sequential time-series data. The model is trained on company-wise historical stock price data from 2000 to 2025, enabling it to understand temporal market behaviors and forecast future prices more accurately. This project addresses key challenges in investment decisions by analyzing multiple factors such as stock price trends, volatility, and performance indicators. It seeks to maximize returns while minimizing risk through optimal allocation of portfolio weights. The system takes real stock datasets as input, preprocesses the data to handle missing values and outliers, and feeds the cleaned data into the LSTM model for training and prediction. The final portfolio recommendations are generated using the predicted returns and risk metrics. The proposed solution offers several advantages: automation of stock analysis, minimization of human biases, adaptability to large datasets, and improved forecasting accuracy. Furthermore, it includes a user-friendly interface that allows investors to visualize model performance, compare predictions with actual stock prices, and simulate investment outcomes.

This project not only serves as a valuable tool for individual and institutional investors but also contributes to the broader field of financial technology (FinTech) by demonstrating the practical application of Deep Learning in stock market forecasting and portfolio management.

I.INTRODUCTION

Stock price prediction and investment portfolio optimization are two of the most crucial challenges in the field of computational finance. Financial markets are highly volatile, non-linear, and influenced by a wide range of factors such as economic indicators, corporate performance, investor sentiment, and global events. Traditional statistical methods like autoregressive models and fundamental/technical analysis have long been used to forecast stock movements. However, these methods often fail to capture the complex, dynamic, and non-stationary nature of financial time series data. With the rapid growth of computing power and the availability of vast amounts of market data, deep learning approaches have emerged as powerful tools for financial forecasting.

Self-Propelled Computational Models (SPCM) powered by deep learning enable researchers and investors to model hidden patterns in stock market data, identify long-term dependencies, and improve the accuracy of predictions. Techniques such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), and Transformers have demonstrated superior performance over Conventional models by effectively handling sequential dependencies and noise in financial datasets. Moreover, the integration of deep learning with reinforcement learning and portfolio optimization frameworks provides investors with strategies that not only predict prices but also suggest optimal asset allocation, risk minimization, and return maximization.

The significance of SPCM in stock market applications lies in its ability to bridge the gap between raw financial data and actionable investment strategies. By leveraging historical price movements, technical indicators, and even alternative data sources such as social media sentiment and news articles, deep learning models enhance predictive capabilities and support real-time decision-making. This integration of stock price prediction with portfolio optimization ultimately empowers investors to achieve a balance between risk and return, ensuring a more resilient and profitable investment strategy. Hence, the application of SPCM: A Deep Learning Approach for Stock Price Prediction and Investment Portfolio Optimization holds great promise in reshaping the future of intelligent financial decision-making.

II.LITERATURE SURVEY

Research in stock price prediction and portfolio optimization has gained momentum with the advent of machine learning and deep learning techniques. Traditional approaches, such as the Efficient Market Hypothesis (EMH) proposed by Fama, argued that stock prices follow a random walk and are difficult to predict accurately. However, subsequent studies demonstrated that historical price patterns, trading volumes, and market sentiment could be leveraged for predictive modeling. Early statistical methods such as Autoregressive Integrated Moving Average (ARIMA) and GARCH models were widely used for time-series forecasting, but they often failed to capture the nonlinear and dynamic patterns of financial data. With the rise of artificial intelligence, researchers began applying machine learning models such as Support Vector Machines (SVMs), Random Forests, and Gradient Boosting to improve prediction accuracy.

In recent years, deep learning models have shown superior performance in financial forecasting. Recurrent Neural Networks (RNNs) and their advanced variants like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) have been extensively applied to capture long-term dependencies in sequential financial data. For instance, Fischer and Krauss (2018) demonstrated that LSTM networks significantly outperformed traditional machine learning models in predicting stock returns. Similarly, Selvin et al. (2017) compared CNN, RNN, and LSTM models for stock prediction and found that hybrid deep learning approaches enhanced forecasting reliability. In parallel, Transformer-based architectures have been introduced, enabling attention mechanisms to capture contextual relationships in high-dimensional financial datasets.

Alongside prediction, portfolio optimization has been addressed through both classical and modern approaches. The Markowitz Modern Portfolio Theory (MPT) laid the foundation for optimal asset allocation by balancing risk and return. However, deep learning-based reinforcement learning frameworks such as Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) have recently been integrated into portfolio management, allowing models to adapt dynamically to market changes. Studies by Jiang et al. (2017) and Zhang et al. (2020) highlighted how deep reinforcement learning can outperform traditional portfolio selection methods by continuously learning from evolving market conditions.

Furthermore, hybrid models that combine sentiment analysis of financial news and social media with price-based models have provided more robust insights into investment decisions.

Overall, the literature indicates a clear evolution from traditional econometric models to advanced deep learning and reinforcement learning techniques. The convergence of stock price prediction and portfolio optimization through deep learning frameworks like SPCM represents a significant leap forward, enabling investors to extract actionable intelligence from complex financial data while addressing both predictive accuracy and investment profitability.

III.EXISTING SYSTEM

The existing systems for stock price prediction and portfolio optimization largely rely on traditional financial theories and machine learning models. Conventional forecasting techniques such as Random Walk Theory, Efficient Market Hypothesis (EMH), ARIMA models, and GARCH models have been widely applied to stock market prediction. These methods are based on statistical and econometric assumptions, often assuming linearity and stationary of financial time series. While these models can capture basic trends and volatility patterns, they fail to effectively handle the nonlinear, dynamic, and noisy nature of financial data. In addition to statistical methods, machine learning algorithms such as Support Vector Machines (SVMs), Random Forests, k-Nearest Neighbors (kNN), and Logistic Regression have been employed to improve prediction accuracy. These models offer better adaptability than traditional econometric models, but they often struggle with long-term dependencies in sequential data and require manual feature engineering. Moreover, most existing systems treat stock prediction and portfolio optimization as separate problems. Prediction systems focus mainly on forecasting future stock movements, while portfolio optimization systems rely on classical approaches like Markowitz Modern Portfolio Theory (MPT) and Capital Asset Pricing Model (CAPM), which optimize risk-return trade-offs but assume normally distributed returns and static market conditions.

Another limitation of existing systems is their inability to incorporate unstructured data sources such as news sentiment, social media discussions, and macroeconomic indicators. Some hybrid models have attempted to integrate sentiment analysis with stock prediction, but they remain limited in scalability and accuracy. Furthermore, many existing portfolio optimization models are not adaptive, meaning they cannot dynamically rebalance portfolios in response to real-time market fluctuations. Overall, the existing systems provide a baseline for financial forecasting and investment strategies, but they suffer from major drawbacks such as low accuracy in volatile conditions, limited integration of multiple data sources, lack of dynamic adaptability, and separation of prediction and optimization tasks. These shortcomings highlight the need for a more robust, integrated, and intelligent framework like SPCM, which leverages deep learning to unify stock price prediction and portfolio optimization under a single adaptive system.

IV. PROPOSED SYSTEM

The proposed system, SPCM (Stock Price and Capital Management), introduces an integrated deep learning framework that combines stock price prediction with investment portfolio optimization in a unified, adaptive, and intelligent platform. Unlike existing systems that treat prediction and optimization separately, SPCM leverages the strengths of deep learning architectures to model complex, nonlinear relationships in financial data and dynamically guide investment decisions. At its core, the system employs advanced deep learning models such as Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), and Transformer-based architectures, which are particularly effective for time-series forecasting. These models capture long-term dependencies, temporal patterns, and hidden structures in stock price data, enabling more accurate and robust predictions even in highly volatile market conditions. Additionally, the system integrates sentiment analysis from news articles, financial reports, and social media feeds, allowing it to account for market psychology and external events that influence investor behavior. For portfolio optimization, SPCM goes beyond traditional theories like Markowitz MPT and CAPM by implementing reinforcement learning (RL) and deep Q-learning strategies. These approaches enable the model to simulate dynamic trading environments and continuously rebalance portfolios to maximize returns while minimizing risks. By learning through trial and error, the system can adaptively adjust portfolio weights in response to real-time market fluctuations, risk levels, and investor preferences.

Another innovative feature of the proposed system is its multi-objective optimization capability. It considers not only return maximization but also factors such as risk exposure, liquidity constraints, and transaction costs, making the portfolio more practical for real-world investment scenarios. Furthermore, the system is designed with a modular and scalable architecture, allowing seamless integration of additional data sources like macroeconomic indicators, volatility indexes, and global financial events.

The proposed SPCM framework is also equipped with a decision-support dashboard, which provides investors with visualizations, risk analytics, prediction confidence levels, and recommended portfolio allocations. This enhances transparency and investor confidence, reducing reliance on intuition-based or speculative decisions.

V.SYSTEM ARCHITECTURE

The diagram illustrates a deep learning-based quantitative model for stock price prediction and portfolio optimization. It is divided into two main components: the Prediction Model and the Optimization Model. On the left side, under the Prediction Model, the process begins with Input Data, which includes historical stock prices, financial indicators, and market information. This data is processed using an LSTM model (Long Short-Term Memory network), which is highly effective for capturing temporal dependencies in stock price time-series data. The LSTM model generates predictive outputs that feed into two sub-models: the Alpha model (which estimates expected returns) and the Risk model (which evaluates associated risks such as volatility). These two models together contribute to Portfolio Construction, ensuring that both expected performance and risk factors are considered in selecting assets.

On the right side, under the Optimization Model, the constructed portfolio undergoes Portfolio Optimization using multiple strategies. These strategies include EQ (Equally Weighted portfolios), MSC (Minimum Standard Deviation or Minimum Variance Strategy), and MVO (Mean-Variance Optimization, based on Markowitz theory). The optimized results are then subjected to Portfolio Evaluation, where the performance, stability, and risk-return balance of the portfolio are assessed. Finally, the system outputs an Optimal Portfolio, which balances predictive insights from the LSTM model with optimization techniques to provide robust investment recommendations.

In summary, the figure represents a hybrid framework that integrates deep learning (LSTM) with quantitative financial models.

It combines prediction accuracy (through Alpha and Risk models) with portfolio optimization techniques (EQ, MSC, and MVO), resulting in an intelligent system capable of generating an adaptive and optimal investment portfolio.

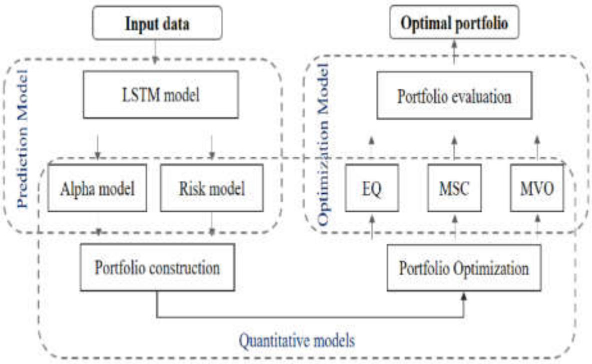

Fig 5.1 System Architecture

VI.IMPLEMENTATION

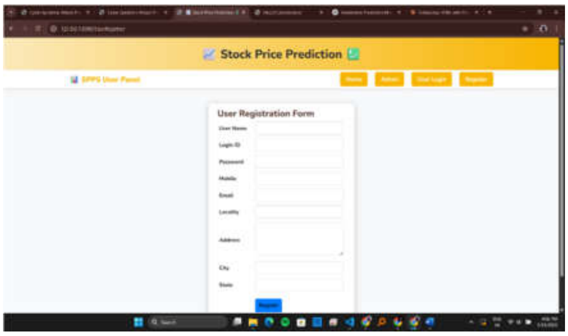

Fig 6.1 User Register

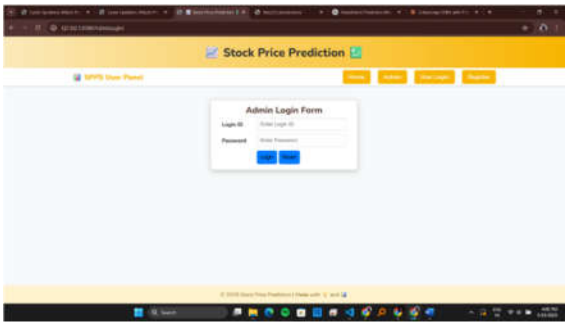

Fig 6.2 Admin Login

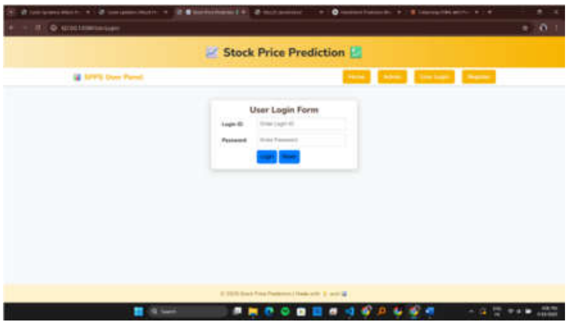

Fig 6.3 User Login

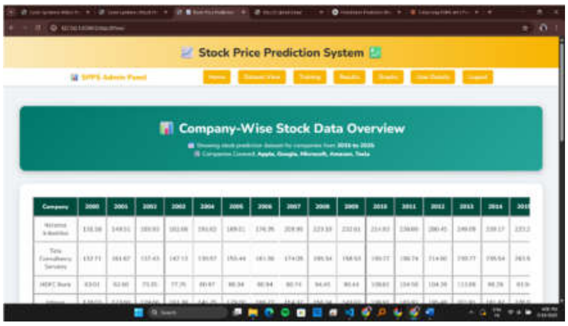

Fig 6.4 View Dataset

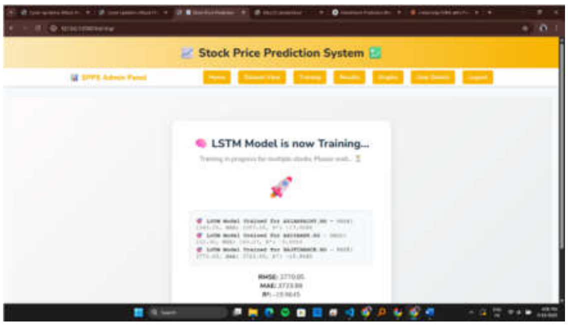

Fig 6.5 Train LSTM model

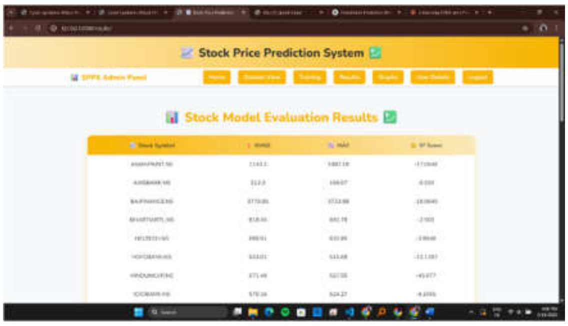

Fig 6.6 Prediction

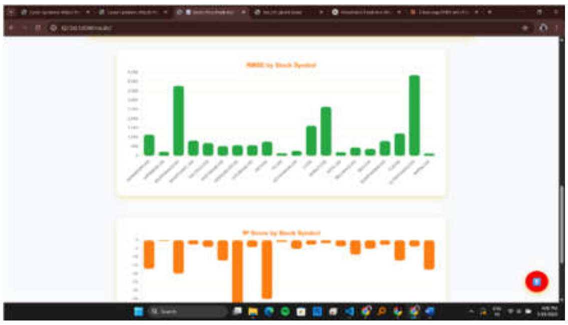

Fig 6.7 Graphs Representation

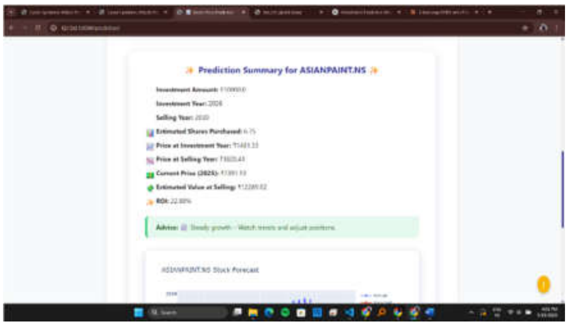

Fig 6.8 Prediction of the stock

VII.CONCLUSION

This project demonstrated the effectiveness of using Deep Learning (LSTM) in optimizing stock portfolios by analyzing historical data and predicting future stock prices. The model improved traditional static methods by dynamically adjusting to market trends. Through prediction, optimization, and visualization, this system provides a modern tool for financial decision-making with high accuracy and reliability. It sets a foundation for future advancements such as reinforcement learning, real-time market feeds, and integration with trading platforms.

VIII.FUTURE SCOPE

The future scope of SPCM: A Deep Learning Approach for Stock Price Prediction and Investment Portfolio Optimization is highly promising, as advancements in artificial intelligence and financial technology continue to evolve. With the rapid growth of big data, integrating larger datasets such as real-time news feeds, social media sentiment, macroeconomic indicators, and alternative data sources can significantly enhance the accuracy of prediction models. Incorporating advanced deep learning architectures like Transformer models, Graph Neural Networks (GNN), and Reinforcement Learning can further improve stock price forecasting and dynamic portfolio rebalancing. Additionally, the framework can be extended to include personalized investment strategies tailored to individual risk appetites and financial goals, making it more applicable for retail investors. From a practical standpoint, the integration of blockchain and decentralized finance (DeFi) mechanisms could bring greater transparency and security to portfolio optimization. Moreover, hybrid systems combining machine learning with traditional econometric approaches could yield more resilient predictions during periods of high volatility, such as financial crises. Ultimately, the model holds potential for deployment as an automated advisory system or robo-advisor, supporting investors and financial institutions in making data-driven, adaptive, and intelligent investment decisions in an ever-changing market environment.

IX.REFERENCES

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