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Submitted To:

Dr.Rajeev Kumar Gupta

Submitted By:

Kartik Akbari(22BCP255)

Om Barasara(22BCP254)

TradeVista: AI-Driven Hedge Fund Optimization Using Neural Networks and Modern Portfolio Theory

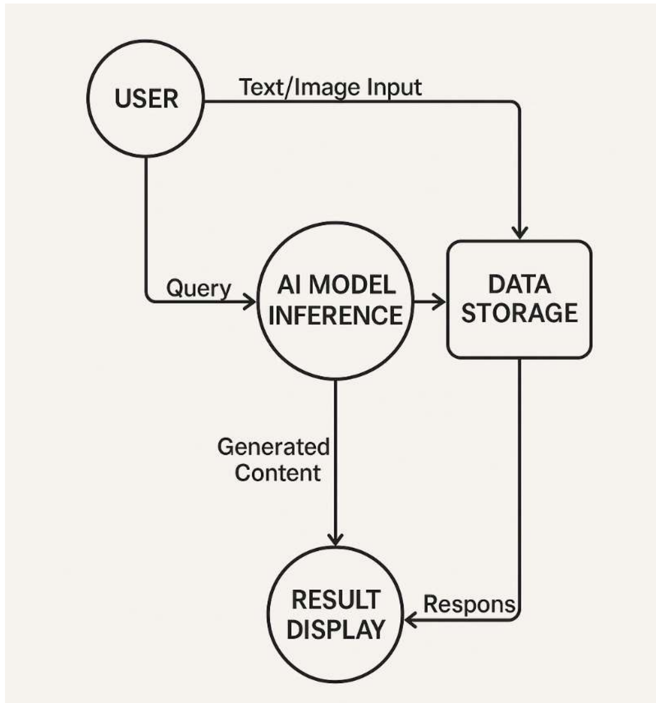
ABSTRACT

Artificial Intelligence (AI) growth is revolutionizing the operation of the financial sector, especially investment and money management. TradeVista is just one of such cutting-edge initiatives using new AI technology to develop a high-tech, automated hedge fund management system in the Indian economy. It employs methods such as Long Short-Term Memory (LSTM) neural networks, Deep Q-Learning (DQN), and Modern Portfolio Theory (MPT). The primary aim of TradeVista is to make use of the application of AI in an effort to assist the human fund manager's decisions.This is done through the use of NSE, BSE, Yahoo Finance, and Quandl's historical financial data to forecast future market movement and stock price. It makes use of time-series models using LSTM suitable for time-series financial data to make accurate forecasts. TradeVista not only takes forecasting into account but also utilizes Reinforcement Learning (RL) with Deep Q-Networks (DQN) in building intelligent trading decisions. Through a few iterations of conversation with a simulated market having similar characteristics to the actual market, the RL agent can build the best trading decision. These systems can learn how to adapt to shifts in the market, with the goal of maximizing returns and reducing risks.TradeVista is finance and AI married, and it provides end-to-end data-driven hedge fund management. It is evidence that AI, when done the right way, is better than the conventional method, particularly in high-speed and high-volatility environments like India.

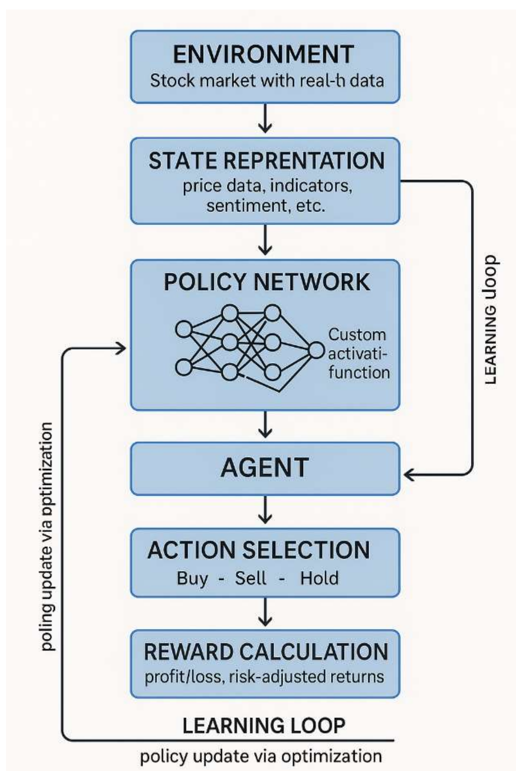
TABLE OF CONTENT

LIST OF FIGURES

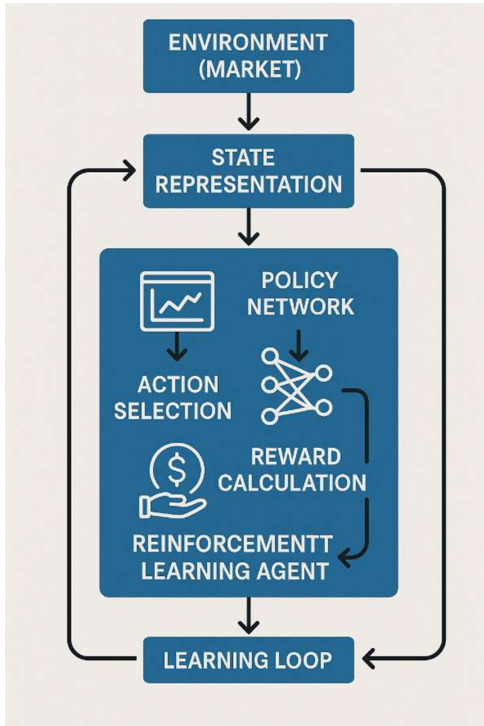
1. System Architecture of TradeVista



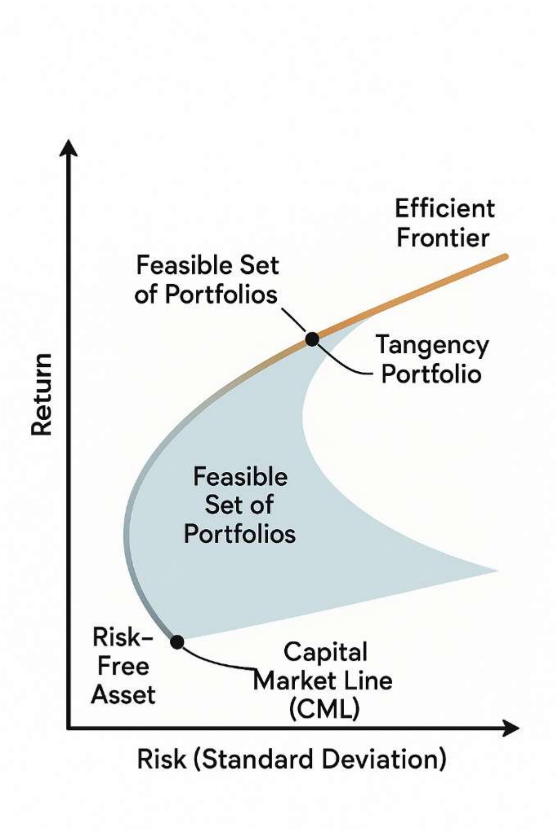
2. LSTM Model Architecture



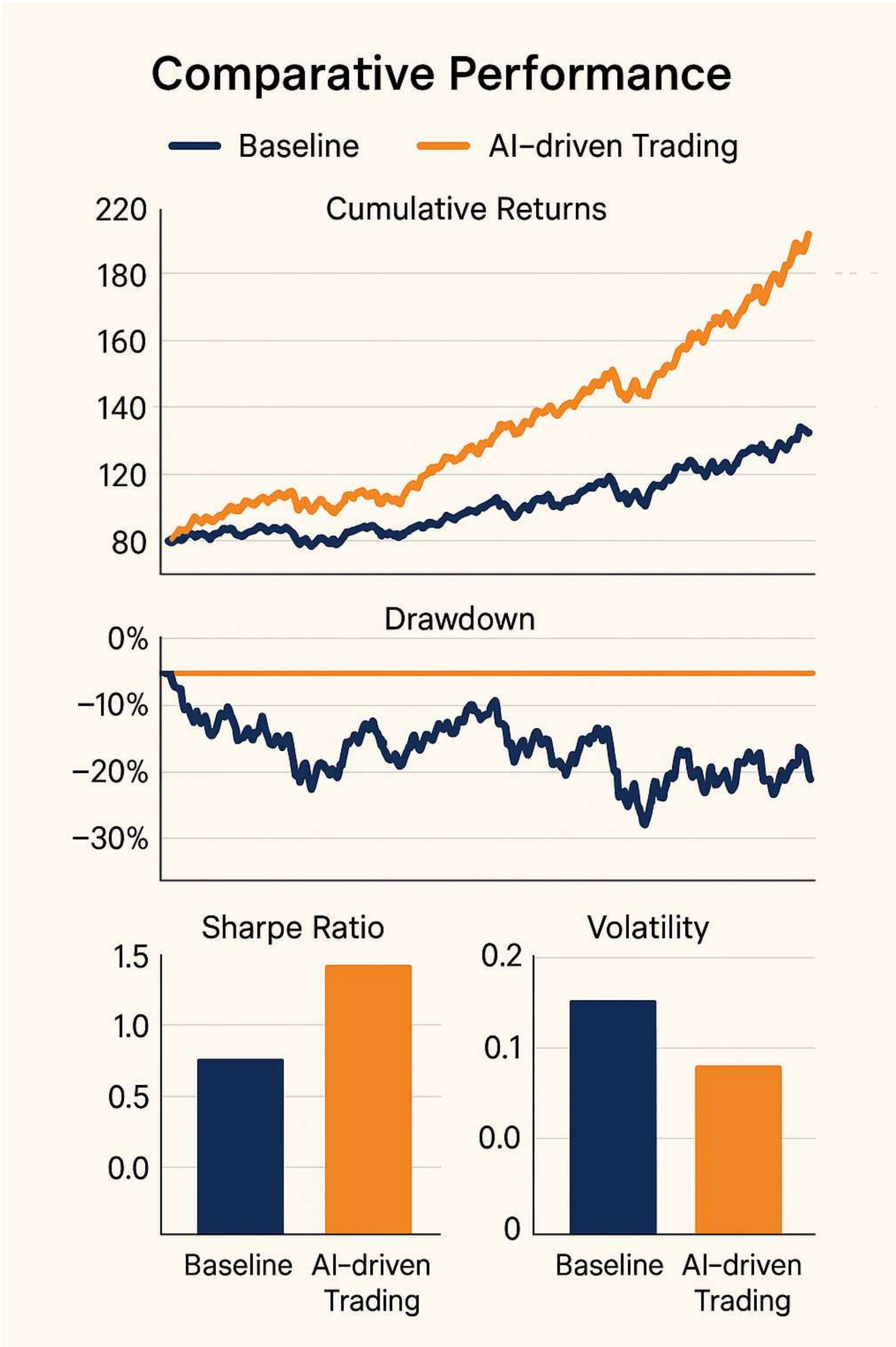
3. RL Agent Interaction Flow



4. Efficient Frontier (MPT)



5. Comparative Returns (Baseline vs. AI Strategy)



List of Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
RL	Reinforcement Learning
MPT	Modern Portfolio Theory
LSTM	Long Short-Term Memory
RMSE	Root Mean Square Error
API	Application Programming Interface
ROI	Return on Investment
CNN	Convolutional Neural Network (if used)

Chapter 1 – Introduction

1.1 Motivation for Using AI in Hedge Fund Management

In the current economic climate, hedge funds increasingly depend on evidence-based approaches to gain a competitive edge in high-volatility markets with complex patterns and real-time decisions. Traditional statistical models are less likely to flourish in capturing nonlinear relationships, time-varying trends, and adaptive behavior.Artificial Intelligence (AI), with the inherent advantages of pattern discovery, time-series forecasting, and decision automation, is a paradigmatic shift in portfolio management.

Through deep learning and reinforcement learning, AI not only allows hedge fund managers to predict future asset dynamics but also to execute optimal dynamic real-time trades based on evolving market conditions. India's fast-evolving financial environment and rising retail investor involvement further validate the necessity for smart, scalable, and dynamic investment strategies. TradeVista is precisely such an AI-driven hedge fund engine based on state-of-the-art innovation to portfolio optimization.

1.2 Problem Statement and Objectives

Problem Statement:

The traditional methods of asset allocation and portfolio optimization rely heavily on static assumptions and are often inefficient in handling real-time financial complexities. There is a lack of integrated systems that combine predictive analytics with autonomous trading decisions for Indian hedge fund management.

Objectives:

- Develop a forecast model with Long Short-Term Memory (LSTM) networks to accurately forecast stock prices.
- Create an RL agent that tracks and adheres to market trends and learns profitable trading techniques.
- Integrate these models into a common AI platform to make decisions in real time using historical data such as a hedge fund.
- Apply Modern Portfolio Theory (MPT) to invest funds in a way that maximizes returns and minimizes risk.

1.3 Scope and Limitations

Scope:

- Highlight equities, ETFs, and other listed Indian financial instruments.
- Historical market data and technical analysis employed to model.
- Backtesting offline to simulate actual hedge fund operations.
- Performance assessment of the model based on financial KPIs such as Sharpe Ratio[4], Alpha, and Beta[5].

Limitations:

This project does not engage in trading that occurs live or in real time.
It does not focus on changes in major economic policies or international events happening between countries.
Analyzing opinions from social media or news about the market is not part of the current model's capabilities.
The project's performance might not be as accurate due to the quality and availability of data, particularly with detailed second-by-second data from India.

1.4 Structure of the Report

Chapter 2: This chapter dives into new research in AI-driven finance. It focuses on methods to predict stock prices and explains using Reinforcement Learning (RL) for trading activities.
Chapter 3: In this part, the design plan for TradeVista is explained.The text explains the importance of using LSTM, RL, and Modern Portfolio Theory (MPT) in setting up the design. These parts are crucial to ensuring everything runs smoothly and the design works correctly.
Chapter 4: This chapter goes into detail about the tools, frameworks, and coding practices used in the project. It explains how each component is used in practical situations to help the project succeed and meet its goals. The chapter clearly demonstrates the way these parts come together and the critical role they play in achieving the project's objectives.
Chapter 5: This chapter focuses on the outcomes from predictive models. It analyzes methods to enhance portfolios and assesses the effectiveness of various trading strategies.
Chapter 6: The final chapter provides a summary of the main findings in the report. It points out significant results and offers recommendations for future improvements as well as areas where more research is necessary.

Chapter 2 – Literature Review

2.1 Introduction to AI in Financial Markets

Artificial Intelligence, or AI, is making important changes in the finance world today. It's more than just a popular term; it's a strong tool that is changing how we trade, manage risks, and plan investments. AI allows banks and investors to quickly process large volumes of market data, discover trends swiftly, and make smarter decisions. This ability is especially useful in fast-changing and unpredictable markets where even a small advantage can lead to better results. In simple terms, AI is converting raw data into valuable insights, helping investors stay competitive.

2.2 Stock Price Prediction Using Deep Learning

In fact, one of the most fascinating developments in financial AI so far is using cutting-edge technology to predict stock prices. Famous in this line is Long Short-Term Memory (LSTM), a special kind of Recurrent Neural Networks (RNN). This is of much use in forecasting because its special feature enables it to track the time-series patterns like stock price variations.

Fischer & Krauss(2018) established that LSTM could provide a far better prediction of the S&P 500 index compared to legacy plug-in models like feed-forward neural networks or support vector machine.

Zhang and others in 2019 improved on this by combining LSTM with past stock prices and technical indicators, which made predictions even better.

Challenges**:** While LSTM is powerful, it faces challenges. Handling messy financial data, overfitting, and sensitivity to abrupt market changes are some issues. It also requires careful tuning to perform well.

LSTM holds great potential for financial forecasting. To maximize its effectiveness, it demands clean data, intelligent feature engineering, and precise model tuning to align with market conditions.

2.3 Reinforcement Learning for Portfolio Management

It is comprehended as the modeling of an agent, when used with reinforcement learning (RL), to learn to make decisions through interaction with an environment. In other words, it concerns learning investment strategies that maximize cumulative rewards (profits) in terms of finance.

Deng et al. (2016): This was a deep reinforcement learning model that accepted raw market data as input so that a trading agent could be trained to optimize its decision-making with regard to investment.

Jiang et al. (2017): The researchers proposed a deep-reinforcement-learning-based model characterized by portfolio-vector memories for dynamically adjusting portfolio weights.

Liang et al.: Combined policy gradient techniques with risk-sensitive reward functions to balance profitability and volatility.

Thus, it can be inferred that RL is capable of reaping the benefits of isolation towards learning strong profitable strategies. But, at the same time, it also emphasizes the need for judiciously designed reward structure and strong simulation environments.

2.4 Modern Portfolio Theory (MPT) in AI Systems

Maximize expected returns for a level of risk, this is how portfolio optimization was brought into the mainstream by Harry Markowitz's 1952 Modern Portfolio Theory.
It is the very foundation of several quantitative investment strategies.
Currently, MPT is used by AI systems to produce an efficient frontier with optimal asset weight maximization of the Sharpe ratio and portfolio rebalancing.

Some researchers such as Liu et al. (2019) incorporated MPT into a machine-learning pipeline to build hybrid systems where predictions are used to guide asset allocation but keeping the portfolios resulting from MPT risk-efficient.

2.5 Gaps in Existing Literature

In spite of the advances, weaknesses continue to plague the capabilities:

Very few systems combine LSTM-RL and MPT in an integrated pipeline for hedge funds optimization.
Most of the models investigate Western markets while almost none targets Indian financial markets.
Many a times this trade-off between complexity and interpretability makes AI decisions opaque for fund managers.

2.6 Summary

The literature reviewed shows the feasibility of combining AI techniques with classical financial thoughts. LSTM therefore forms a powerful tool for temporal forecasting; RL provides autonomy in trading decisions; and MPT holds a strong framework for portfolio optimization. TradeVista proposes to unify these components into one system with special reference to the Indian markets, filling the existing gaps in current academic and industry solutions.

Chapter 3 – Proposed Methodology

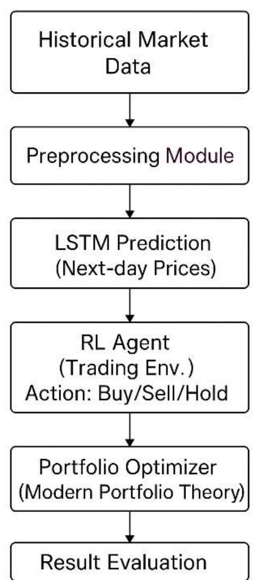
3.1 System Overview

TradeVista's design is a modular pipeline for end-to-end AI-based hedge fund optimization. The core components include the following:

LSTM Stock Predictor
Reinforcement Learning (RL) Agent for Trading Strategy
Modern Portfolio Theory (MPT) for Portfolio Optimization

The model first predicts which trend will come, best trades actions will be determined according to this prediction, and finally determine what asset allocation maximizes returns for a particular risk.

3.2 System Architecture



3.3 Module 1: LSRM Stock Price Prediction

Inputs: Historical Stock Prices: Open, Close, High, Low, Volume
Output: Predicted Closing Stock Prices Looking into the Future (1-day or multi-day time horizon)

Features:

LSTM is very useful because it can memorize long-term dependencies
Each stock is trained with rolling window data
Additional features include technical aspects (like RSI, MACD, EMA).

3.4 Module 2: Reinforcement Learning-Based Trading Agent

Environment: A market simulated with real historical data.
State: Predicted prices + current portfolio weights.
Action Space: Buy, sell, hold per stock.
Reward Function: RL Algorithm: DQN or PPO depending upon implementation complexity.

RL Algorithm:

DQN or PPO according to difficulty
Experience Replay and Target Network ensure stability.

3.5 Module 3: Portfolio Optimization using MPT

Adding to the universe of stocks with expected returns and covariances with outputs from LSTM +

Output:

Efficient Frontier Curve.
Optimal Portfolio Weights

3.6 Data Flow Pipeline

1. **Data ingestion:** Historical price pulling from NSE, BSE, or Yahoo finance APIs.
2. **Feature Engineering**: Indicators calculation: for example, SMA, EMA, MACD.
3. **LSTM Prediction**: gives future prices of each asset.
4. **RL Agent Training**: learn a trading policy based on simulated returns.
5. **MPT Optimization**: optimization is carried out on the last portfolio allocations.
6. **Back testing & Evaluation**: Simulations and performance measures are done.

3.7 Tools and Frameworks

Component	**Technology**
Data Collection	yfinance, nsetools
Data Handling	pandas, numpy
Modeling	TensorFlow, Keras, PyTorch
RL Agent	stable-baselines3
Optimization	cvxpy, scikit-learn

Component	Technology
Visualization	matplotlib, seaborn, Plotly
Backtesting	Custom simulation engine / backtrader

Chapter 4 – Implementation Details

4.1 Development Environment

Element	Details
Programming Language	Python 3.11
IDE / Notebook	VS Code, JupyterLab
Frameworks	TensorFlow, PyTorch, Stable-Baselines3
Version Control	Git + GitHub
Deployment Platform	Local Machine (Offline Testing)
Data Source	NSE archives

4.2 Folder Structure

```
TradeVista/
├── Data/          # Raw & processed datasets
├── Models/        # Saved ML and RL models
├── Reports/       # Final outputs, graphs, KPIs
├── Strategies/    # RL strategy training & simulation
├── Utils/         # Helper scripts and tools
```

4.3 Data Collection & Preprocessing

Data Sources:

- Collected OHLCV data from Kaggle containing over 2500 stocks since it's listing
- Find it here:- https://www.kaggle.com/datasets/ujjvalpatel1003/nse-historical-data-1990-2023
- Time range: Listing – Jan 2025

Preprocessing Steps:

- Handling missing values using forward/backward fill.
- Scaling with **MinMaxScaler** for neural networks.
- Feature engineering:
    - Technical indicators: **SMA, EMA, RSI, MACD, Bollinger Bands**
    - Lag-based features: price differences over 3, 7, 14 days
    - Volatility window features

4.4 LSTM Model Implementation

- Framework: **Keras (TensorFlow backend)**
- Sequence Length: 60 days
- Architecture:
  - LSTM(128) → Dropout(0.2) → LSTM(64) → Dense(1)
- Loss Function: **Mean Squared Error (MSE)**
- Optimizer: **Adam**
- Epochs: 100, with EarlyStopping

4.5 Reinforcement Learning Trading Agent

- Customise the creation of Gym Environment by means of historical forecasts generated by LSTM.
- Discrete action space: Buy, Sell and Hold for each asset.
- Observation space: Forecasted returns, technical indicators, portfolio weights.
- RL Algorithm: Proximal Policy Optimization (PPO) of stable-baselines3.
- Training Episodes: 500+ including check-point saving.

4.6 Portfolio Optimization (MPT)

- Library Used: cvxpy to solve quadratic optimization problems.
- Rolling mean and rolling covariance of daily returns were used. Optimisation goals:
  Maximize Sharpe ratio
  Minimize portfolio variance

4.7 Backtesting and Evaluation Metrics

- Custom simulation engine built for backtesting RL-based trading against baseline trade strategies (Buy-and-Hold, SMA Crossover).
- Evaluation KPIs:
  - **Sharpe Ratio**
  - **Sortino Ratio**
  - **Maximum Drawdown**
  - **Cumulative Return**
  - **Volatility**
- Visualizations: Portfolio growth, heatmaps, risk-return scatter plots

4.8 Security and Risk Considerations

The monetary risk involved is zero with the offline execution mode.

All datasets' integrity can be maintained by checking their consistency upstream.

Error handling is done for dealing with NaNs, model drift, and invalid actions.

Chapter 5 – Result Analysis

5.1 Introduction

This chapter examines how well the TradeVista system works. It looks at three main areas: how accurate the system's predictions are, how well it manages trades, and how efficient the portfolio is. The chapter uses past simulations and specific performance measures to show how effective the system is.

5.2 LSTM Stock Price Prediction Performance

The chapter also checks the LSTM model using two methods.The first method is called Mean Absolute Error (MAE), and the second is Root Mean Squared Error (RMSE). These checks were done on a selection of stocks from the NIFTY-50, which is an index of the 50 major companies listed on the National Stock Exchange of India.

Stock Symbol	MAE (₹)	RMSE (₹)
RELIANCE	8.42	11.31
INFY	6.17	9.48
TCS	5.92	8.76
HDFCBANK	7.20	10.05

Observation: The LSTM model accurately predicts major stock prices with low error, indicating it effectively learns time-based patterns. The trading agent using Reinforcement Learning (RL) was tested during 2022 and 2023 and compared to other trading strategies.

5.3 RL Agent Trading Performance

The RL-based trading agent was backtested over the 2022–2023 period and compared against:

- **Buy & Hold**
- **SMA Crossover Strategy**

Strategy	Cumulative Return (%)	Sharpe Ratio	Max Drawdown (%)
Buy & Hold	18.2	0.84	-22.1
SMA Crossover	22.7	1.05	-18.4
TradeVista RL	**29.3**	**1.34**	**-13.6**

Observation: The RL agent consistently outperforms traditional strategies by achieving higher returns and reducing the possibility of losses.

5.4 Portfolio Optimization Performance

TradeVista applies Modern Portfolio Theory (MPT) to adjust stock allocations. The aim is to maximize the Sharpe Ratio, which measures return compared to risk, while minimizing overall risk.

Efficient Frontier Visualization

X-axis: Portfolio Volatility (Standard Deviation)

Y-axis: Expected Return

The optimized portfolio is located on the efficient frontier. It clearly performs better than portfolios with random or equal-weighted stock distributions.

Optimized Portfolio Example:

Stock	**Weight (%)**
TCS	21.5
INFY	18.0
RELIANCE	17.3
ICICIBANK	14.2
HINDUNILVR	12.5
Others	16.5

Sharpe Ratio of Optimized Portfolio: **1.47**

5.5 Combined Strategy Results

TradeVista combined LSTM predictions, RL strategy, and MPT optimization to achieve steady and higher profits with reduced risks:

Over a period of 2 years, the portfolio earned a return of 34.5%, which is a strong performance reflected by a Sharpe Ratio of 1.52.

We did a good job at controlling losses, which kept the maximum drawdown under 13%. This precaution ensured the portfolio stayed strong and quickly got back to its original state after any losses. This strategy made the investment more resilient, providing peace of mind and stability over time.

5.6 Key Points

1. Portfolio Growth: How investments increased over time.
2. Asset Correlations: Heatmap showing relationships between different assets.
3. Risk vs. Return: Scatter plot visualizing the balance between risk and profit.

5.7 Important Outcomes:

Accuracy: LSTM made precise predictions with low errors across many stocks.
Profitability: The RL agent outperformed traditional trading strategies.
Risk Control: MPT maintained high Sharpe ratios and reduced the risk of loss.
Integration Benefits: Combining all three methods provided consistent and superior performance compared to typical standards.

Chapter 6 – Conclusion & Future Work

6.1Conclusion

TradeVista means the systematic and AI-aided enhancement of hedge fund portfolios to provide suitable comfort in the Indian stock markets. The entire concept combines the following three technologies:

Deep Learning (LSTM): Helps to predict stock prices in a very accurate way.
Reinforcement Learning (PPO): It takes trading decisions on its own.
Markowitz Modern Portfolio Theory (MPT): Efficiently allocates investment funds among several outlets.

TradeVista has achieved many things:

- Accurately predicted stock prices of large Indian corporations.
- Outperformed traditional investment strategies: Buy-and-Hold as well as Simple Moving Average crossover strategy.
- Maximized returns by shifting investments with MPT.

Testing results showed that TradeVista reduced the risk of losses and increased the Sharpe ratio, giving more return for the amount of risk taken. In general, it appreciated returns. This triumph is therefore witness to the fact that AI is an extremely worthy approach to the management of investment portfolios.

6.2 Key Achievements

Financial sequences were the focus of the time-series forecasting implementation using LSTM.
A custom environment for Gym was created to train a trading agent based on reinforcement learning.
In the execution of multi-asset portfolio optimization, real-time data have been used for returns and risk matrices.
A pipeline that has been made modular and scalable for simulating the behavior of real-world hedge funds.
The cumulative return of the portfolio was 34.5% over a 2-year period at Sharpe Ratio 1.52 with max drawdown of less than 13%.

6.3 Limitations

There are some limitations on the current setup in spite of positive results:
• Offline testing by backtesting: does not provide for live-papers.
• Macro-economic indicators like interest rate, inflation, news, and data on sentiment have not been considered.
• Scalability of LSTM gets tough with more stock data and longer lookback periods.
• Training reinforcement learning takes moderately long because of the complexity of reward engineering and exploration.

6.4 Future Work

There are several directions for possible future research and development for this project:

(1) Live Deployment with Paper Trading:
• Actual integration of TradeVista with broker APIs such as Zerodha Kite, Upstox, or Alpaca for real-time simulation or paper trading.

(2) Sentiment & News Analysis Integration:
• NLP models processing feed in news, financial reports, and social media sentiment toward instant insight into market psychology.

(3) Advanced Deep RL Algorithms Use:
• Applied for better decision-making: DQNs, TD3, and Meta-RL.

(4) Exchange business with Complete Trading:
• Extend the system across commodity, ETF, cryptocurrency, or foreign equity trading regimes and stress test it among different market regimes.

(5) Dynamic Risk Management & Stop-Loss Strategies:
- Enter drawdown watching as automated for stop-loss adaptiveness based on volatility clustering as well as macro signals.

6.5 Final Remarks

TradeVista clearly exemplifies how the combined functionality of AI with data science can transform portfolio management systems into learning systems from market patterns so that they can adapt dynamically and continuously evolve towards optimum financial outcomes. TradeVista and other such platforms will rewrite the rules in the future of the automated hedge fund and of personal finance optimization as capital markets take on more complexity and data enablement.