SDP FINAL EVALUATION

Revolutionizing Portfolio Management in the age of Generative AI

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Group No. Q7

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Presentation Outline

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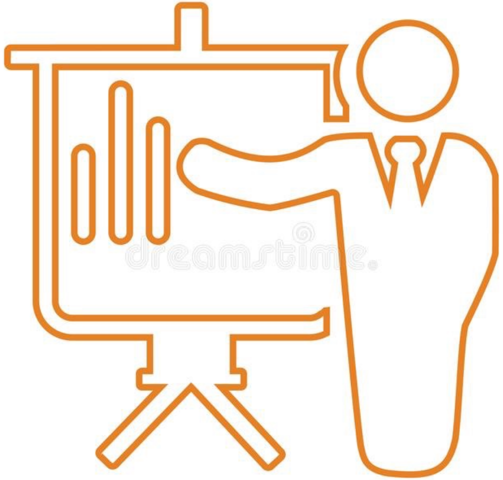


Introduction

Overview

- Traditional portfolio management has relied on human expertise and heuristics to select assets and optimize portfolios.

- The combination of **deep reinforcement learning (DRL)** and **generative adversarial networks (GANs)** provides a robust framework for portfolio management.

- The aim of the project is to revolutionize portfolio management in the age of **Generative AI** and demonstrate the potential of DRL and GANs to improve portfolio performance and manage risk.

- This approach enables the creation of **synthetic data** that can be utilized to train an agent, resulting in improved investment decision-making.

Introduction contd..

- **Our work is aimed at producing stock prediction based on historical dataset**

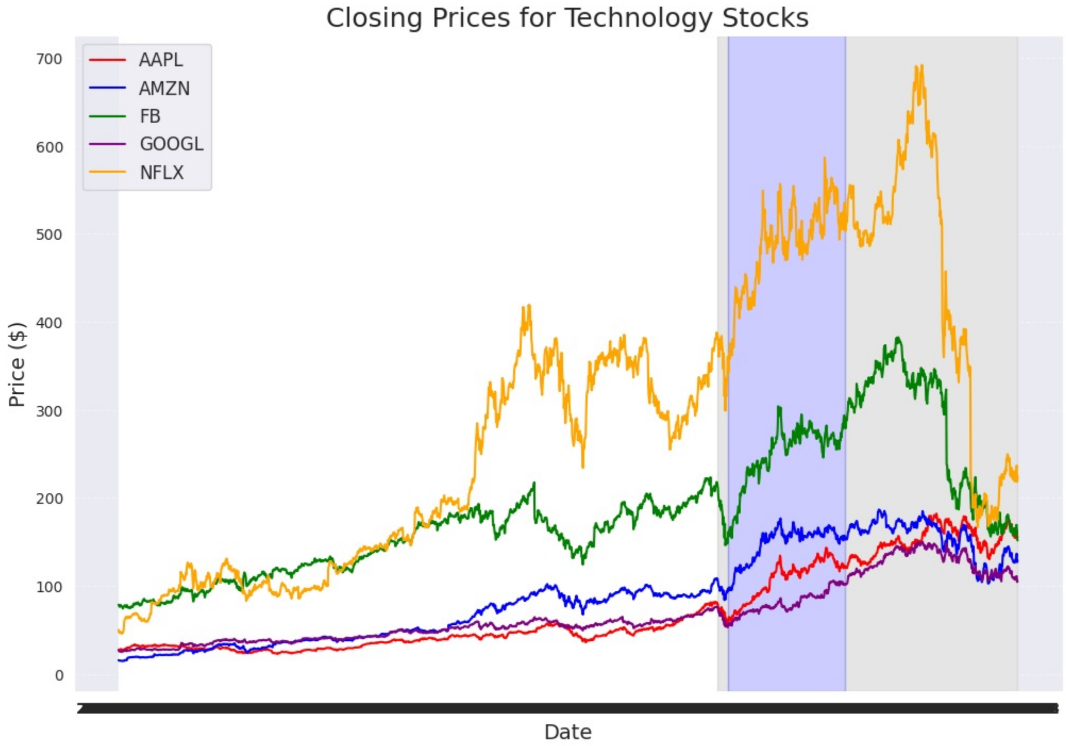


Fig:1 - Dataset Visualization

Introduction contd..

Motivations

- Traditional portfolio management relies on heuristics and human expertise, which may not be optimal or efficient.
- Suboptimal portfolio management has led to significant losses in the past, emphasizing the need for more advanced and efficient methods.
- The combination of DRL and GANs offers a more sophisticated and adaptable investment model that can generate better returns and manage risk more effectively.
- Our methodology aims to revolutionize portfolio management in the age of generative AI by demonstrating the potential of DRL and GANs to improve portfolio performance.
- By creating synthetic data that can be used to train an agent, our approach enables improved investment decision-making and better outcomes for investors.

Literature Survey

❑ Existing System

Year	Methodology	Advantages	Limitations
2023 [1]	DRL with Modern Portfolio Theory	Dynamic Asset allocation	Reliance on historical data may not capture the dynamic nature of financial markets.
2023 [2]	Predictive Auxiliary classifier GAN	Measure uncertainty in portfolio optimization and generation of synthetic data	Complexity of the model may prone to overfitting and suffer from a lack of interpretability
2023 [3]	Portfolio allocation on money Net-Flow adjusted using DRL	enhance the decision-making	complexity of the RL architecture make the implementation and training process challenging
2023 [4]	DRL Approach to Portfolio Optimization in the Australian Stock Market	minimizing transaction costs and improving overall portfolio	requires careful calibration and may vary across different DRL algorithms.
2021 [5]	DRL with Latent Feature State Space	Highly Efficient and Performance	Need of large amount of dataset and accurate feature engineering

Table:1 – Existing Systems

Literature Survey contd..

❑ Existing System

Year	Methodology	Advantages	Limitations
2021 [6]	Stock Portfolio Optimization Using a DL LSTM Model	High precision of the LSTM model	Complexity of predicting stock prices
2020 [7]	DRL with Restricted Stacked Autoencoder	Minimizes the market risk and settlement with Blockchain	The use of a blockchain may not be feasible or practical for all investors.
2019 [8]	DRL with Autonomous Trading Agent	Model-based approach that can work with both on-policy and off-policy RL algorithms	Suboptimal performance due to complexity and dynamics of financial markets
2019 [9]	An intelligent financial portfolio trading strategy using deep Q-learning	Efficient Budget Allocation	Data Requirements
2019 [10]	DRL with Hierarchical Risk Parity	Stacking recent performances for decision-making	Limited description of the models and hyperparameters

Table:2 - Existing Systems

Literature Survey contd..

Problem Identification

- Traditional portfolio management relies on human expertise and heuristics, which can be suboptimal and lead to losses.
- Market conditions are constantly changing, making it difficult to adapt and optimize portfolio strategies in a timely manner.

Solution Approach

- Develop a GAN-based synthetic dataset by forecasting market conditions to simulate multiple investment scenarios and reduce the impact of real-time market fluctuations.
- Train a DRL model on the synthetic dataset to identify low-risk high-return investment opportunities and optimize portfolio performance by continuously adapting to evolving market conditions.

Model Diagram

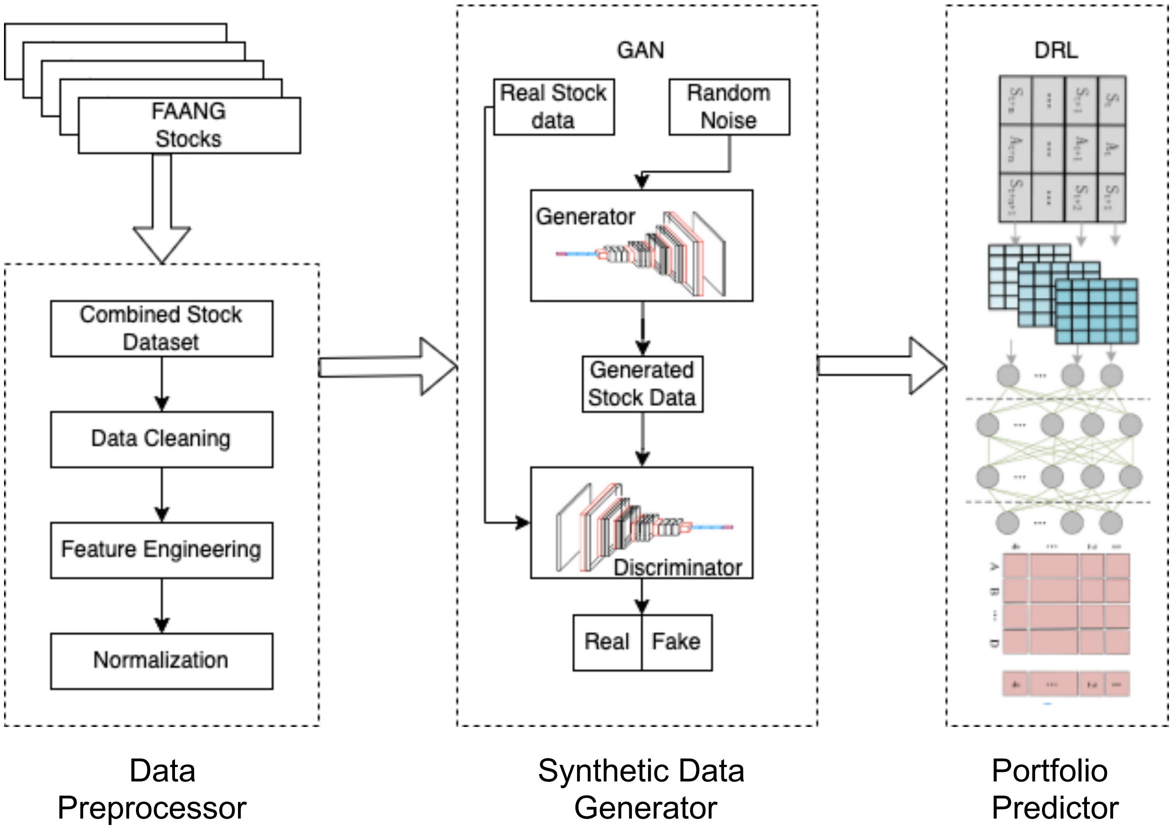


Fig:2 – Model Diagram

Algorithms used in Synthetic Data Generator:

Generative Adversarial Networks (GANs)

- GAN is basically made up of two competing neural network models
- The Generator generates fake data and tries to fool the Discriminator
- The Discriminator tries to distinguish between the real data and fake data

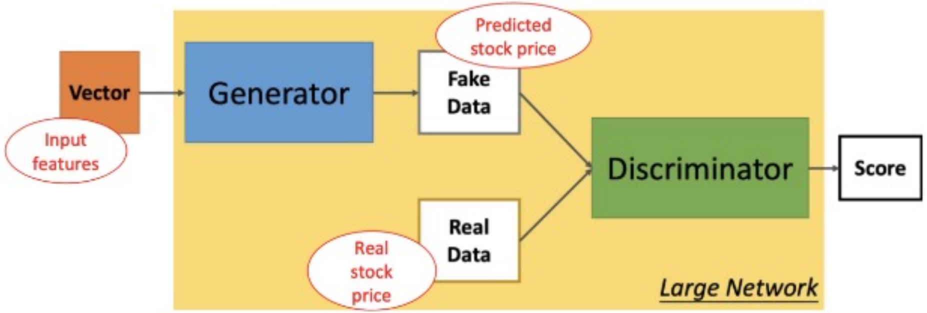


Fig:3 - GAN Architecture

Loss function of Descriminator:

$$-\frac{1}{m}\sum_{i=1}^{m} log\ D(y^i) - \frac{1}{m}\sum_{i=1}^{m}(1 - log\ D(G(x^i)))$$

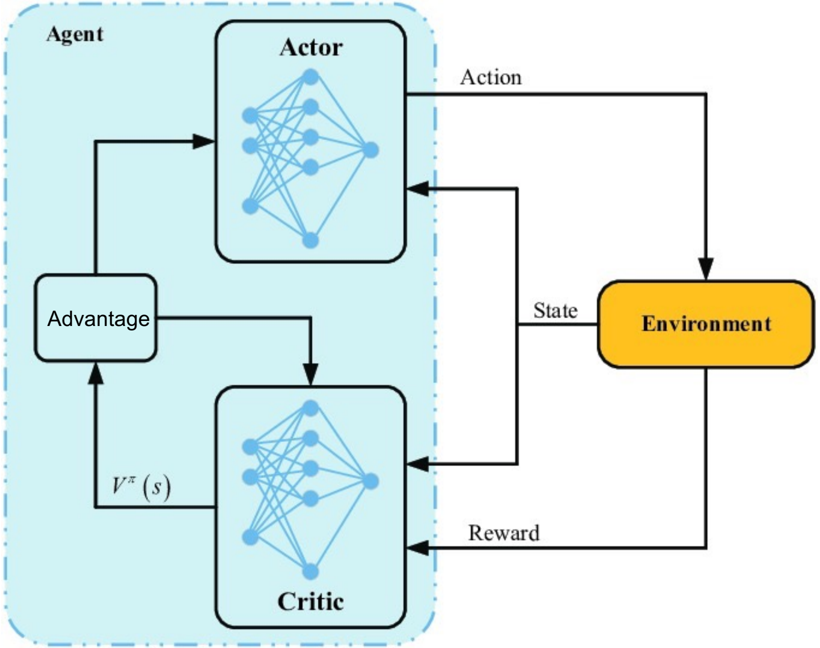
Loss function of Generator:

$$-\frac{1}{m}\sum_{i=1}^{m}(log\ D(G(x^i)))$$

x : Input for generator
y : Real price from original data
$G(x^i)$: Generated price (fake price)

Algorithms used in Portfolio Predictor:

Actor-Critic is a Deep Reinforcement Learning Algorithm with two models actor & critic



Actor Network

Critic Network

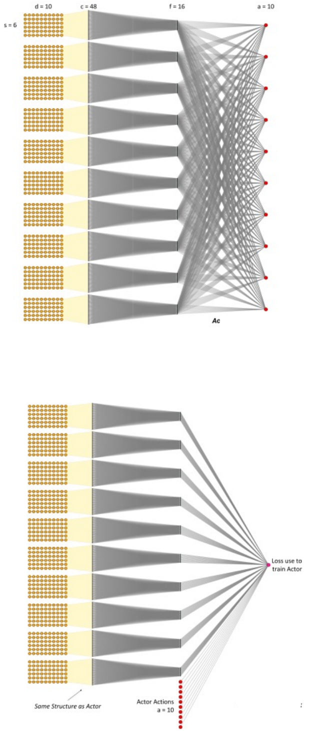


Fig:4 - Deep Actor-Critic Structure

Experimentation and Results

System Specifications

- **Hardware Model** : HP Pavilion Notebook 15-bc5xxx
- **RAM** : 8 GB
- **Processor** : Intel® Core™ i5-9300H CPU @ 2.40GHz × 8
- **OS** : Pop!_OS 22.04 LTS
- **Software Used** : VS Code, Google Colab

Experimentation and Results Contd..

Dataset Description

- The dataset contains the stock data of **FAANG** companies from 1st January 2015. It was sourced from a dataset available on **Kaggle** [11] and **Yahoo Finance** [13] that contains daily stock market data for Facebook, Amazon, Apple, Netflix, and Google.

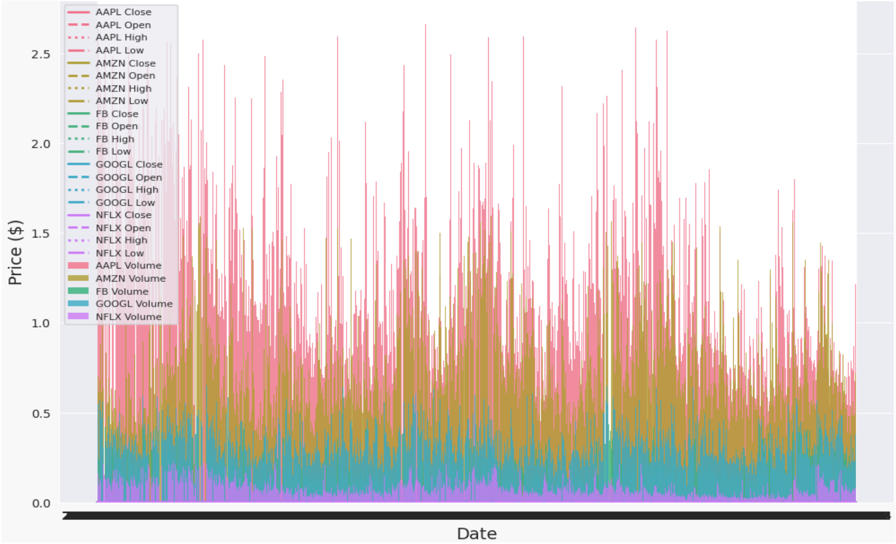


Fig:5 – FAANG Stock OHLCV Data Visualization

Summary statistics:

	Open	High	Low	Close	Volume
count	9700.000000	9700.000000	9700.000000	9700.000000	9.700000e+03
mean	139.417877	141.232668	137.529008	139.428227	5.716630e+07
std	122.988149	124.776052	121.071084	122.943255	5.892155e+07
min	14.310000	14.540000	14.260000	14.350000	0.000000e+00
25%	49.837500	50.197500	49.387500	49.797500	1.683152e+07
50%	103.185000	104.895000	101.720000	103.665000	3.571971e+07
75%	171.255000	173.200000	169.305000	171.272500	8.060547e+07
max	724.440000	724.620000	724.440000	724.620000	6.488252e+08

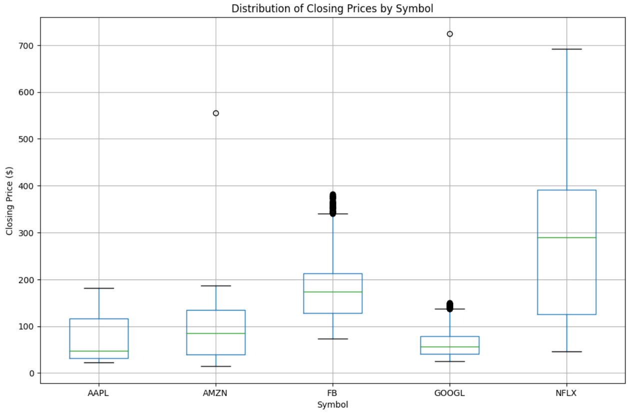
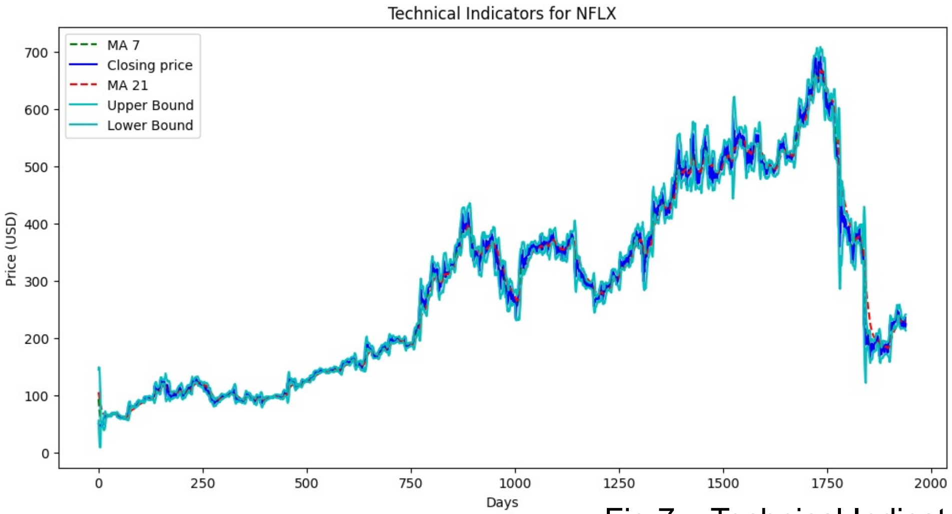


Fig:6 – Box Plot & Summary Statistics

Experimentation and Results Contd..

❑ Parameters used

- **Basic Variables**: Highest Price, Lowest Price, Opening Price, Closing Price, Volume
- **Technical Indicators**: Simple Moving Average (SMA), Exponential Moving Average (EMA), Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), Average True Range (ATR), Bollinger Bands, Raw Stochastic Value (RSV)



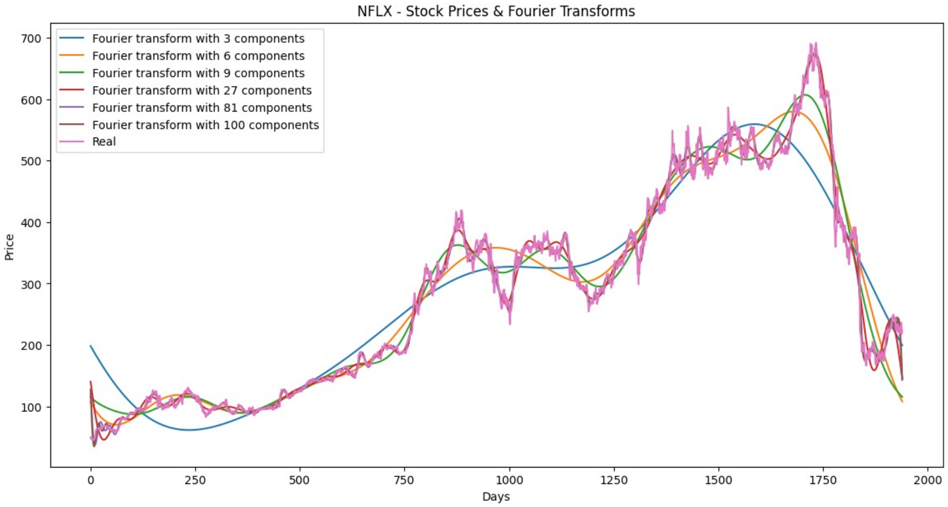


Fig:7 – Technical Indicators and Fourier Transform

Experimentation and Results Contd..

- Experimental outcomes and stocks analysis for FAANG companies

- Facebook(META)
- Amazon
- Apple
- Netflix
- Google

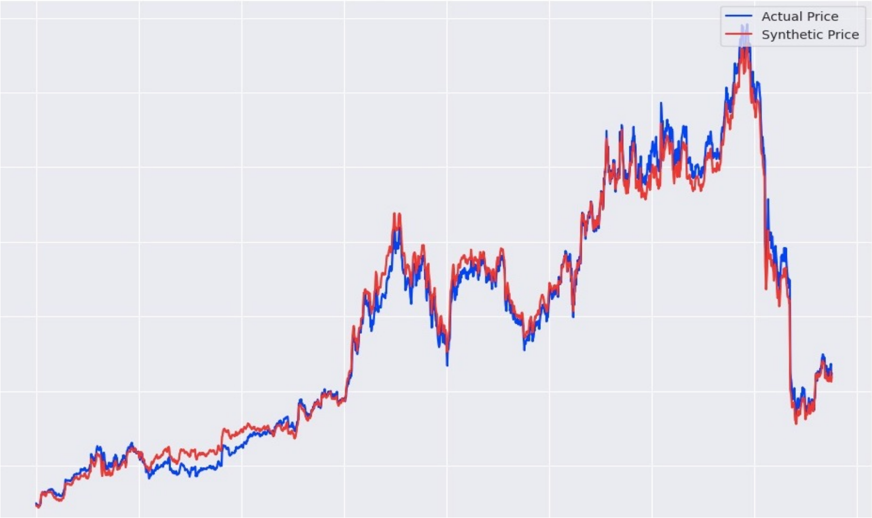


Fig:8 – Actual vs Synthetic stock price

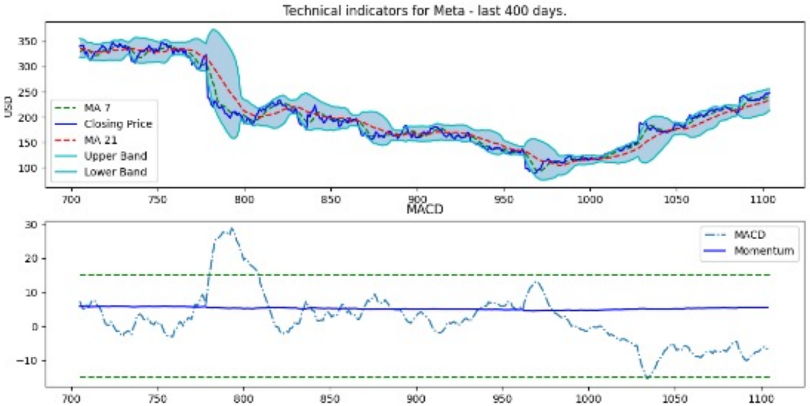


Fig:9 - Facebook Stock

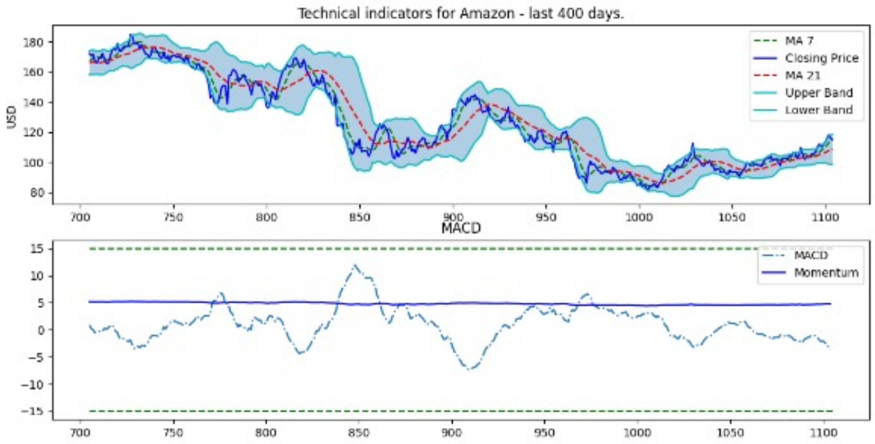
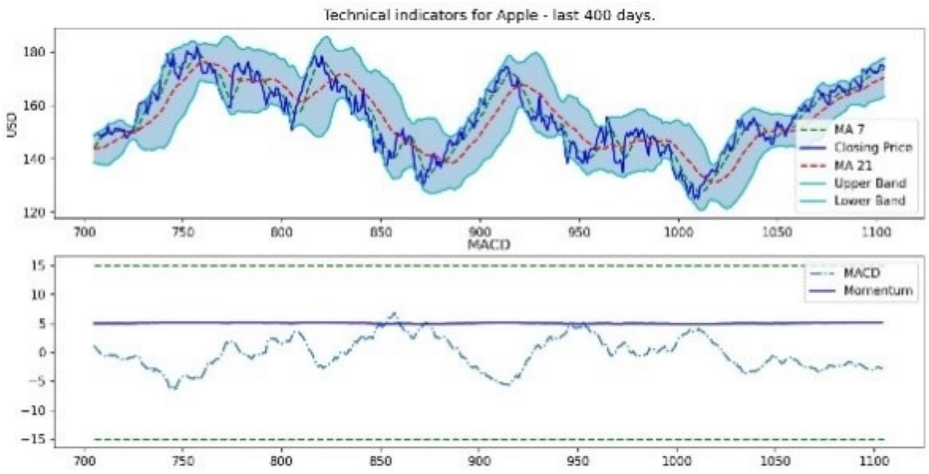


Fig:10 - Amazon Stock



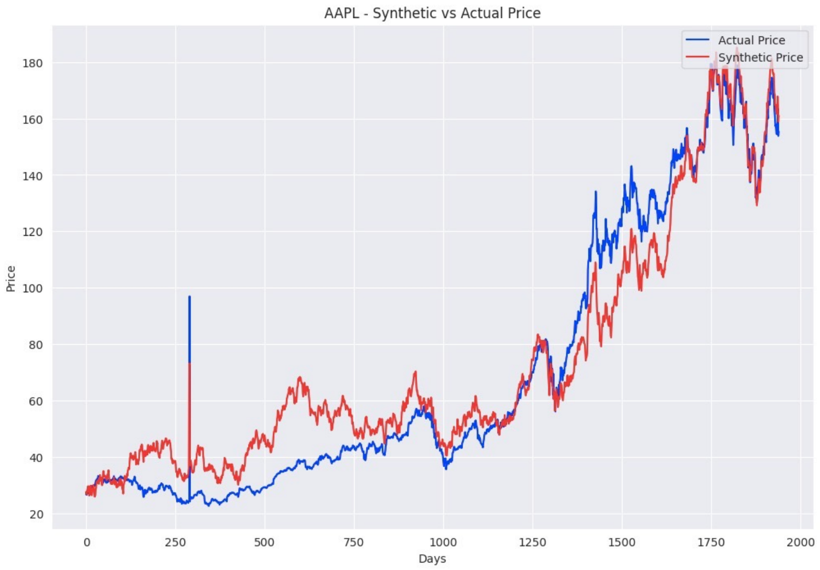


Fig:11 - Apple Stock

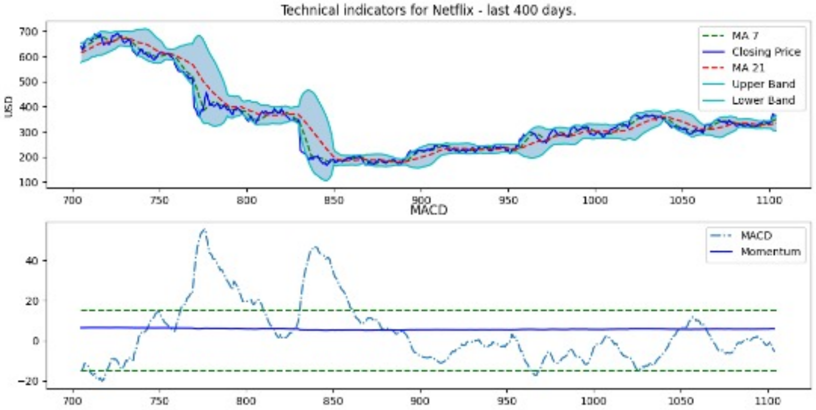
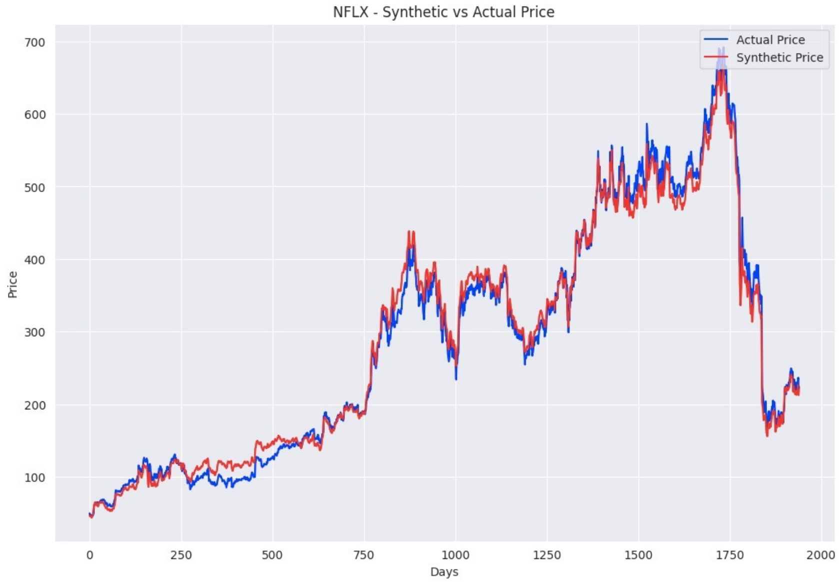


Fig:12 - Netflix Stock



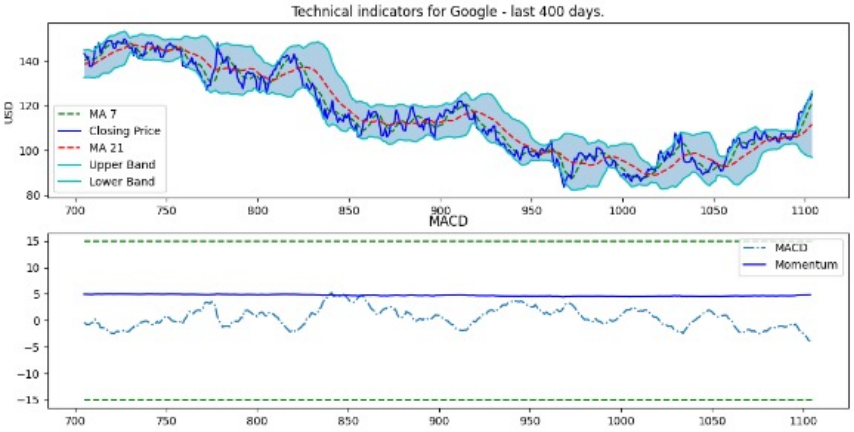


Fig:13 - Google Stock

Result Analysis and Validation

- ➢Statistical parameters (mean, variance, correlation) are used to assess the caliber and fidelity of the generated synthetic datasets compared to the original historical data.

- ➢Relevant statistical metrics like mean squared error and visualization approaches are employed to evaluate the similarity and accuracy of the generated data.

- ➢By incorporating technical indicators from real data, it is confirmed whether the GAN model captures the patterns and characteristics of the financial performance of FAANG enterprises.

- ➢The DRL-based portfolio management strategy achieved significantly higher cumulative returns compared to benchmark strategies, indicating its ability to identify profitable investment opportunities and optimize portfolio allocation.

- ➢The DRL model effectively balanced risk and return, delivering favorable risk-adjusted returns with Portfolio Diversification. Its incorporation of various risk factors contributed to managing portfolio volatility and long-term performance optimization.

Result Analysis and Validation Contd..

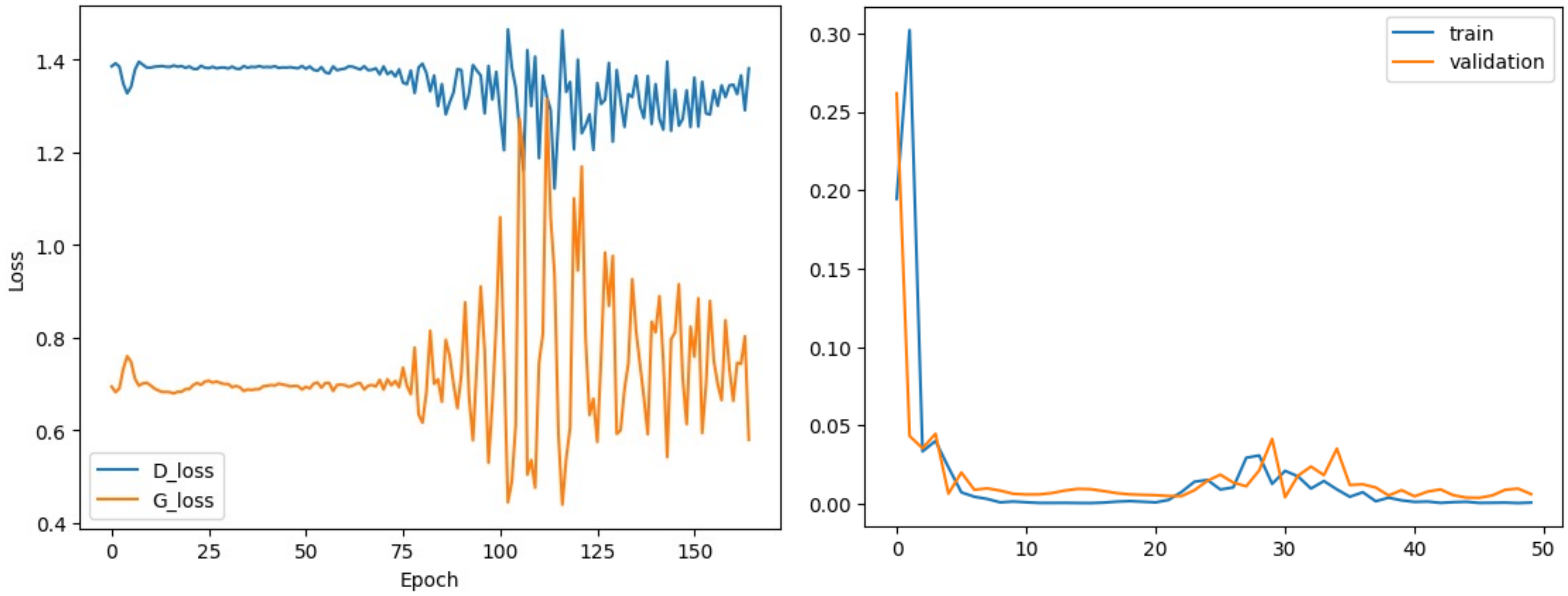


Fig:14 – GAN Loss Plot

Result Analysis and Validation Contd..

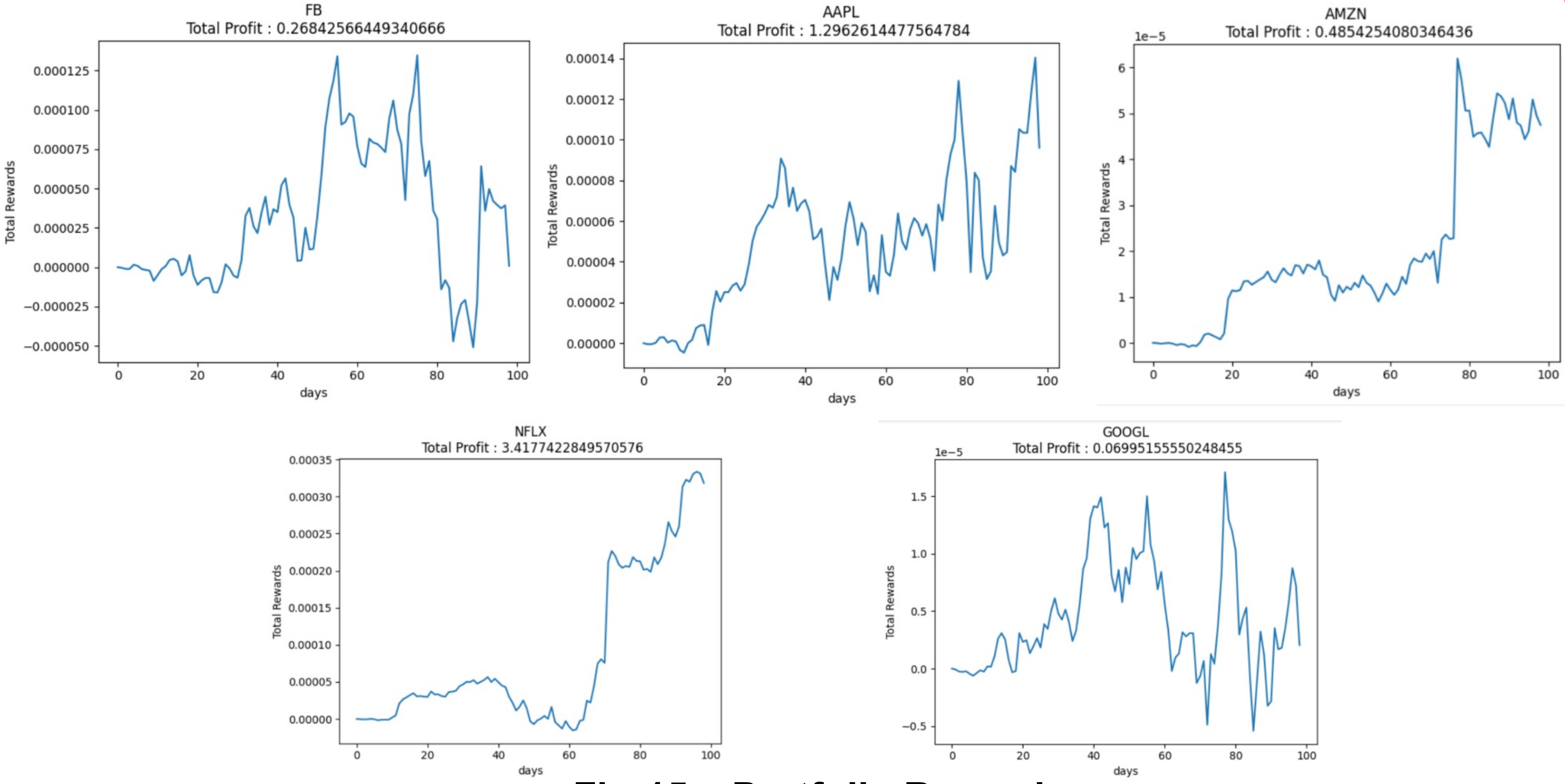


Fig:15 – Portfolio Rewards

Conclusion (Key Findings)

- The proposed system's combined model of DRL (Deep Reinforcement Learning) and GAN (Generative Adversarial Network) outperforms existing systems in terms of performance.
- The system generates synthetic asset returns, enabling improved investment decision-making.
- The model captures complex and non-linear relationships within financial data, enhancing its ability to analyze and predict market dynamics.
- The system incorporates tail risks and extreme events that traditional models often fail to consider, thereby offering a more comprehensive risk assessment.
- By providing better risk-adjusted returns in complex financial markets, the system demonstrates its potential for enhancing investment outcomes. Additionally, it facilitates unbiased decision-making regardless of market conditions.

Future Scope

- Analyze news articles, social media feeds, and other textual data to extract sentiment and assess market sentiment towards FAANG companies, leveraging the use of NLP techniques.
- Conduct additional comparative analysis of the DRL and GAN's combined model with other advanced existing systems, exploring its performance across different market conditions and asset classes.
- Enhance the synthetic asset return generation capabilities of the proposed system by incorporating more sophisticated algorithms and techniques to provide even better insights for investment decisions.

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Thank You