AI-Portfolio-Manager

Explanation Report

1. Approach and Methodology

I worked step by step to build and test an AI-driven portfolio optimization system.

Step 1: Collecting Data
I collected historical financial data (daily price data of selected stocks and indices).
The raw data files are stored in the `data/raw` folder. After cleaning, I stored them in the `data/processed` folder.

Step 2: Preprocessing the Data
I removed missing values, aligned all time series to the same dates, and normalized the input data so that my models could learn patterns more easily.

Step 3: Feature Preparation
I used a sliding window (lookback) to create input sequences.
For each day, I used the previous N days of returns as input to predict the next day's returns.

Step 4: Building Models
I used two deep learning models:
LSTM (Long Short-Term Memory)
Transformer
Both models were trained on the same dataset for a fair comparison.

Step 5: Predictions to Portfolio Weights
The models predict expected returns.
I converted these predictions into valid portfolio weights by:

- Removing negative values
- Normalizing them so that all weights add up to 1

Step 6: Calculating Portfolio Performance
Using the predicted weights, I simulated portfolio returns.
I compared these AI-based strategies against a simple "hold" strategy.

2. Description of Models Used

LSTM (Long Short-Term Memory) Model
The LSTM model is designed to learn from sequences of past returns and predict future returns. It processes data step by step, remembering important patterns while ignoring noise.

Layer	Output Shape	Parameters
LSTM	(None, 60, 50)	16,200
Dropout	(None, 60, 50)	0
LSTM	(None, 50)	20,200
Dropout	(None, 50)	0
Dense	(None, 6)	306

Total Parameters: 36,706

Trainable Parameters: 36,706

Non-trainable Parameters: 0

Transformer Model

The Transformer model uses self-attention to focus on the most important parts of the input sequence. Instead of processing data step by step like an LSTM, it looks at the entire sequence at once and learns which time steps are most relevant.

Layer	Output Shape	Parameters
Input	(None, 60, 30)	0
MultiHeadAttention	(None, 60, 30)	7,936
Add & LayerNormalization	(None, 60, 30)	included
Dense (Feed-Forward 1)	(None, 60, 128)	3,968
Dense (Feed-Forward 2)	(None, 60, 30)	3,870
Add & LayerNormalization	(None, 60, 30)	included
GlobalAveragePooling1D	(None, 30)	0
Dense (Hidden)	(None, 64)	1,984
Dense (Output)	(None, 6)	390

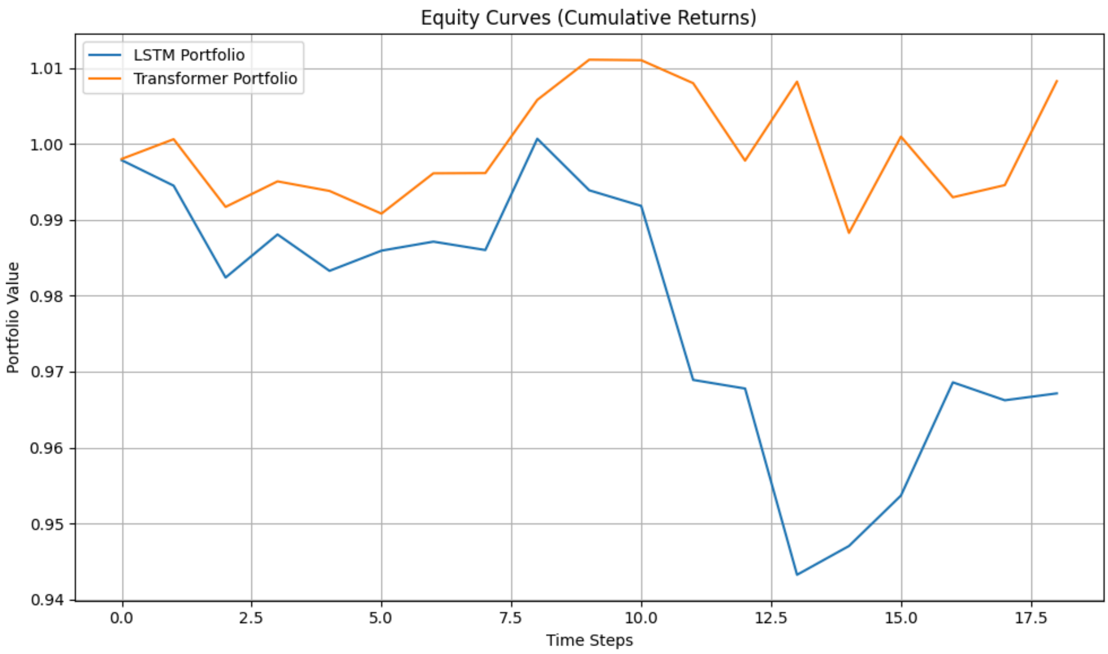
Approx. Total Parameters: ~18,000 (trainable)

3.Challenges Faced and Solutions

Challenge	How I solved it
Missing values in data	I filled or removed missing data and aligned dates.
Models predicting negative values	I clipped negative predictions to zero and re-normalized weights.
Overfitting during training	I used a validation split and early stopping to avoid overfitting.
Managing folder structure in Git	I cleaned up the repository, moved all scripts into `scripts/`, and updated the `.gitignore`.

4. Summary of Results and Metrics

Equity Curves (Cumulative Returns):

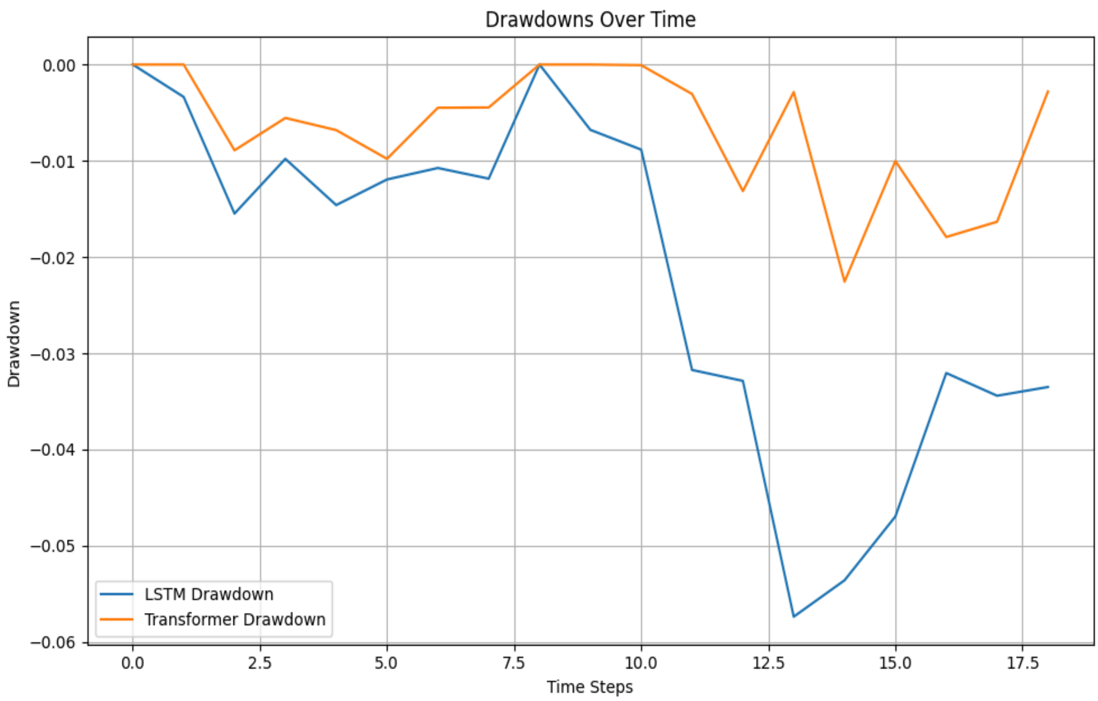


- The blue line represents the LSTM Portfolio over time.
- The orange line represents the Transformer Portfolio.
- This graph shows how the portfolio values change step by step.

Observation:

- The LSTM portfolio shows a noticeable decline after certain time steps, reflecting negative returns.
- The Transformer portfolio performs better overall, maintaining a more stable and slightly increasing cumulative return trend.

Drawdowns Over Time



- The blue line shows the drawdowns for the LSTM portfolio.
- The orange line shows the drawdowns for the Transformer portfolio.
- Drawdown indicates how much the portfolio fell from its peak at each time step.

Observation:

- LSTM drawdowns reach deeper negative levels, indicating higher volatility and larger losses from peak.
- Transformer drawdowns remain smaller and better controlled over time, implying a more stable portfolio.

Performance Metrics Table

Strategy	Annual Return (%)	Volatility (%)	Sharpe Ratio	Max Drawdown (%)
LSTM Strategy	-42.98%	16.04%	-2.68	-5.74%
Transformer Strategy	11.75%	13.07%	0.90	-2.26%

Prediction Performance Table

Model	RMSE (% daily return)	Directional Accuracy (%)
LSTM	3.15%	46.49%
Transformer	8.83%	48.25%

Insights:

- The Transformer Strategy achieved a positive annual return (11.75%) with lower volatility (13.07%) and a Sharpe ratio of 0.90, indicating a more efficient risk–return profile compared to LSTM.
- The LSTM Strategy suffered negative annual returns (-42.98%) and higher drawdowns, showing instability in allocation.
- Prediction-wise, both models showed similar directional accuracy, but LSTM had a slightly lower RMSE than Transformer.