



Genetic Algorithms for Portfolio Strategy Optimization

SCS 3547: Intelligent Agents

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Introduction to the Project



Background:

In the dynamic and complex world of financial markets, predicting stock movements remains a challenging task. Traditional time series methods often fail to capture dependencies and patterns in the data. Advanced models such as Transformer require a lot of time to train the model and optimize the hyperparameters.

Objectives:

This study aims to use the Transformer model for price prediction and use genetic algorithms for hyperparameter optimization to quickly identify the "optimal" model. The result is an effective and computationally efficient forecasting framework that empowers investment portfolios.

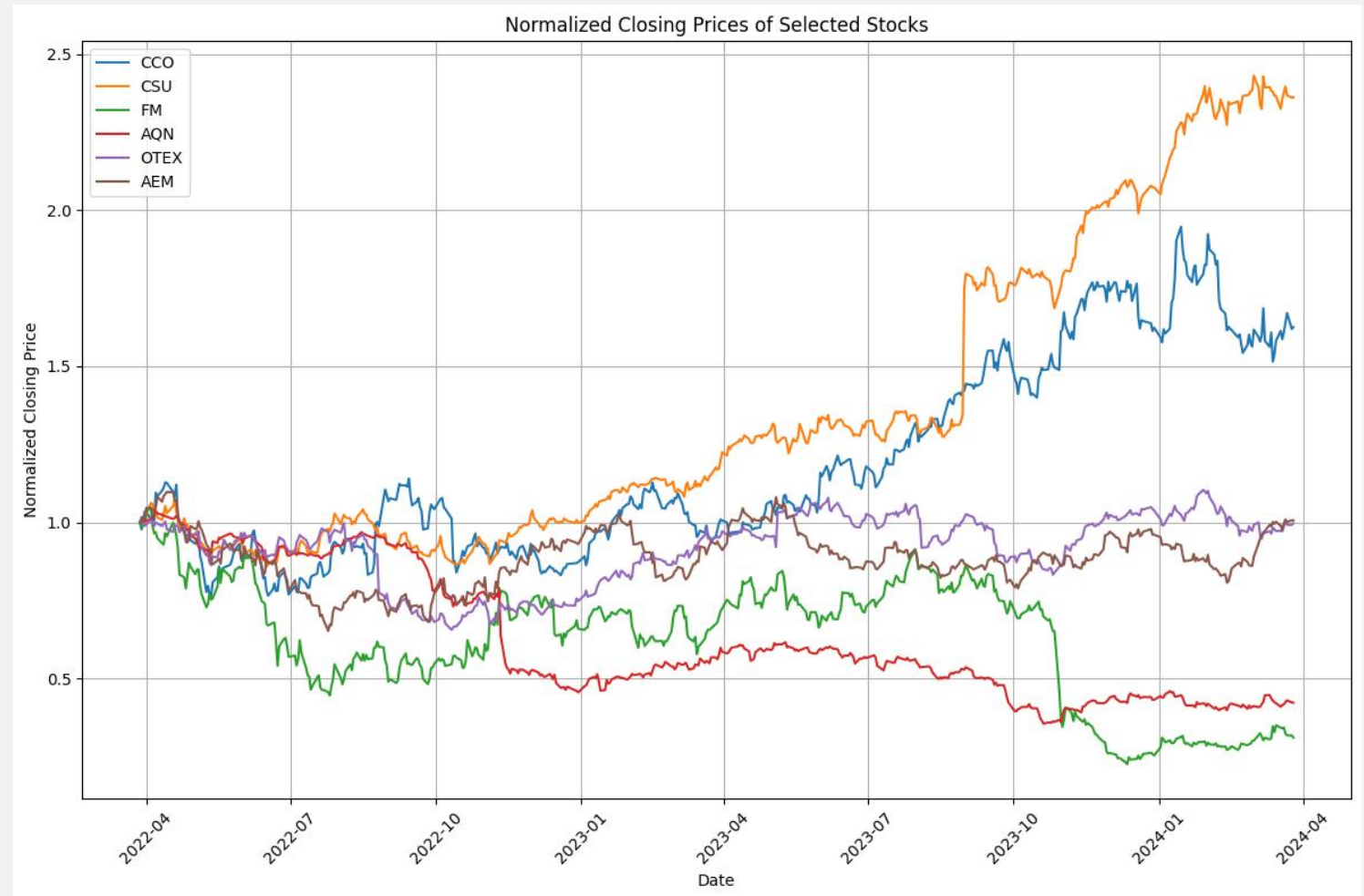
Data Overview

Data Source

1. The stock data set is obtained from IBKR API and collects daily data for 2 years. (highest price, lowest price, opening price, closing price, average, trading volume and number of transactions)
2. The risk-free interest rate refers to the Canadian Overnight Repo Rate Average provided by the Bank of Canada.

Data Processing

1. Technical Indicators:
EMA, RSI, BB, VWAP, ATRP, MFI, VPT, TMI
2. Use Z-Score normalization and choose 20 as the Sequence Length (approximately the number of trading days in a month).
3. Split the dataset:
Train: #386 Days=80%; Test: #97 Days=20%



Note: Stock trends over the past two years among the S&P/TSX 60 (60 large companies listed on the Toronto Stock Exchange) - the 6 stocks with the biggest gainers/fallers, and smallest spreads.

Model Architecture and Training



Transformer

- PositionalEncoding
- TimeSeriesTransformer

Genetic Algorithm

- Uniform Crossover (Pop: 25)
- Mutation (CXPB: 0.7, MUTPB; 0.3, NGEN; 30)
- Selection (Roulette Wheel)
- Early Stopping (5 Epochs)
- Fitness Evaluation(Directional Accuracy & Theil's U(Uncertainty coefficient))
- Parallelizing Computations



Hyperparameters Optimization

- Number of Layers (2 / 4 / 8)
- Number of Heads (2 / 4 / 8)
- Learning Rate (0.01 / 0.05 / 0.1)
- Dropout Rate (30% / 40% / 50%)
- Batch Size (16 / 32 / 64)
- Number of Epochs (30 / 40 / 50)

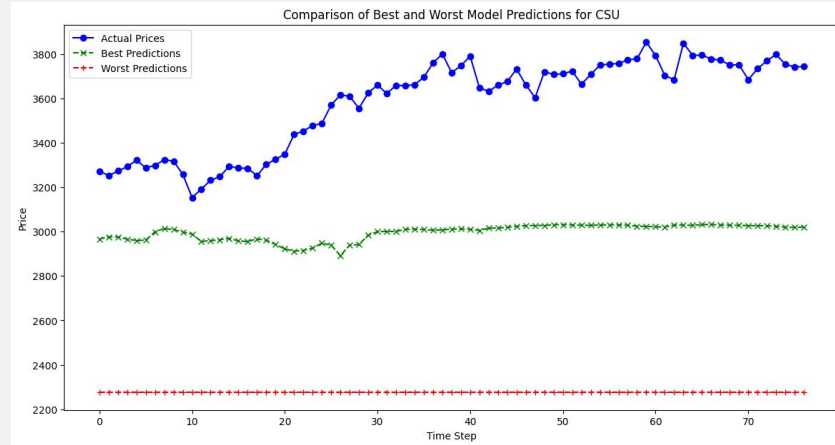


Results

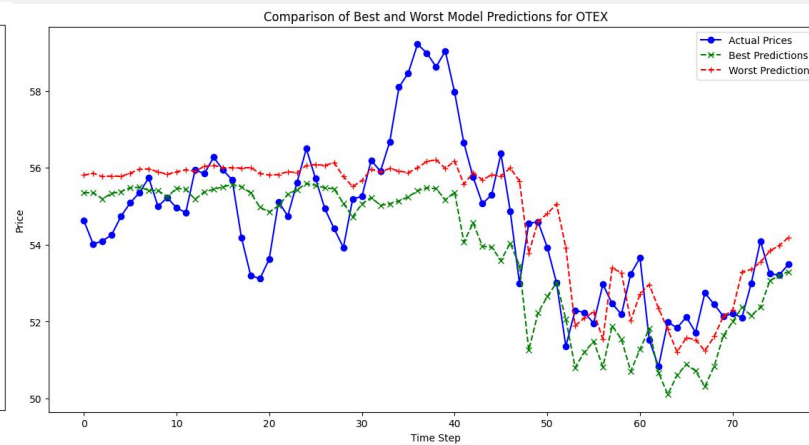
Symbol	Runtime(s)	Type	Fitness Score	num_layers	num_heads	lr	dropout	batch_size	epochs
FM	835.54	Best	0.52532	2	2	10	30	16	30
		Worst	0.51236	4	2	10	50	16	40
OTEX	1442.89	Best	0.64384	2	2	5	40	32	30
		Worst	0.48580	2	2	10	50	64	40
AQN	1366.72	Best	0.47117	4	2	10	50	32	50
		Worst	0.43289	4	4	10	50	16	50
CCO	710.18	Best	0.62857	2	4	10	50	64	30
		Worst	0.52188	4	4	5	50	32	30
CSU	2471.12	Best	0.37553	2	4	10	50	16	40
		Worst	0.35789	4	8	5	50	32	40
AEM	1207.21	Best	0.60442	2	2	1	40	64	30
		Worst	0.40577	4	4	5	30	64	40

Performance Evaluation

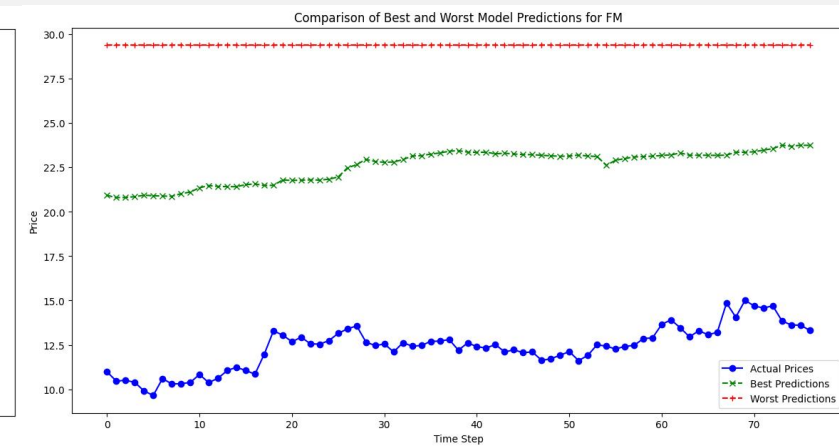
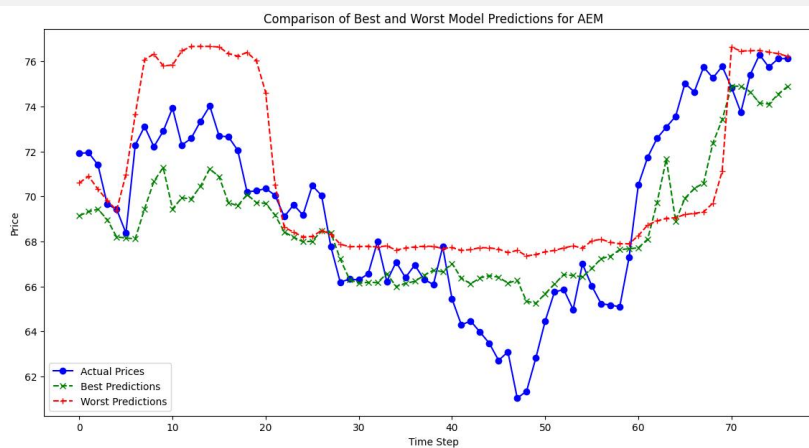
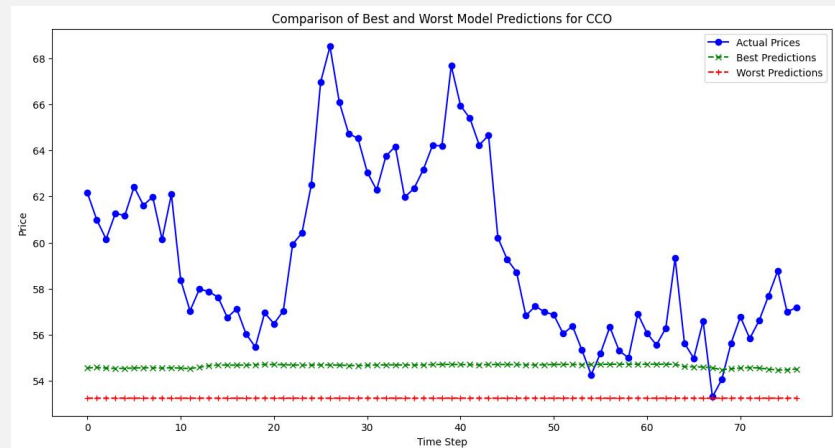
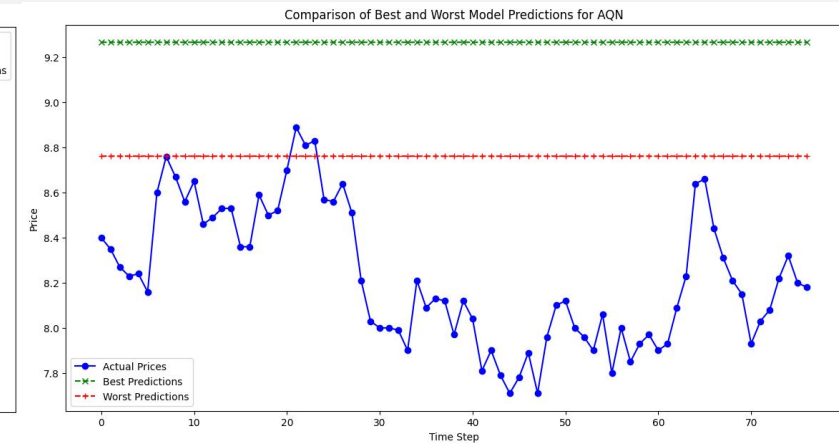
Biggest Gainers



Smallest Spreads



Biggest fallers



Conclusions

This study successfully demonstrates the potential of combining Transformer models with genetic algorithms. By utilizing the advantages of the Transformer model to analyze time series data and the search efficiency of the genetic algorithm, the computational overhead is significantly reduced while improving prediction accuracy.

Future Work:

01

Adaptive Sequence:

If the model can be trained on multiple sequence lengths, it will enable it to learn both short-term and long-term trends, allowing it to make more informed predictions.

02

Enhanced Population Diversity:

A larger population size can introduce more genetic diversity and provide a wider search space for the algorithm.

03

Optimization Complexity:

Implementing more efficient hyperparameter optimization techniques (e.g. using continuous values) may lead to better convergence to an optimal solution.



THANKS FOR WATCHING

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