Stock Price PREDICTION

Team Members:

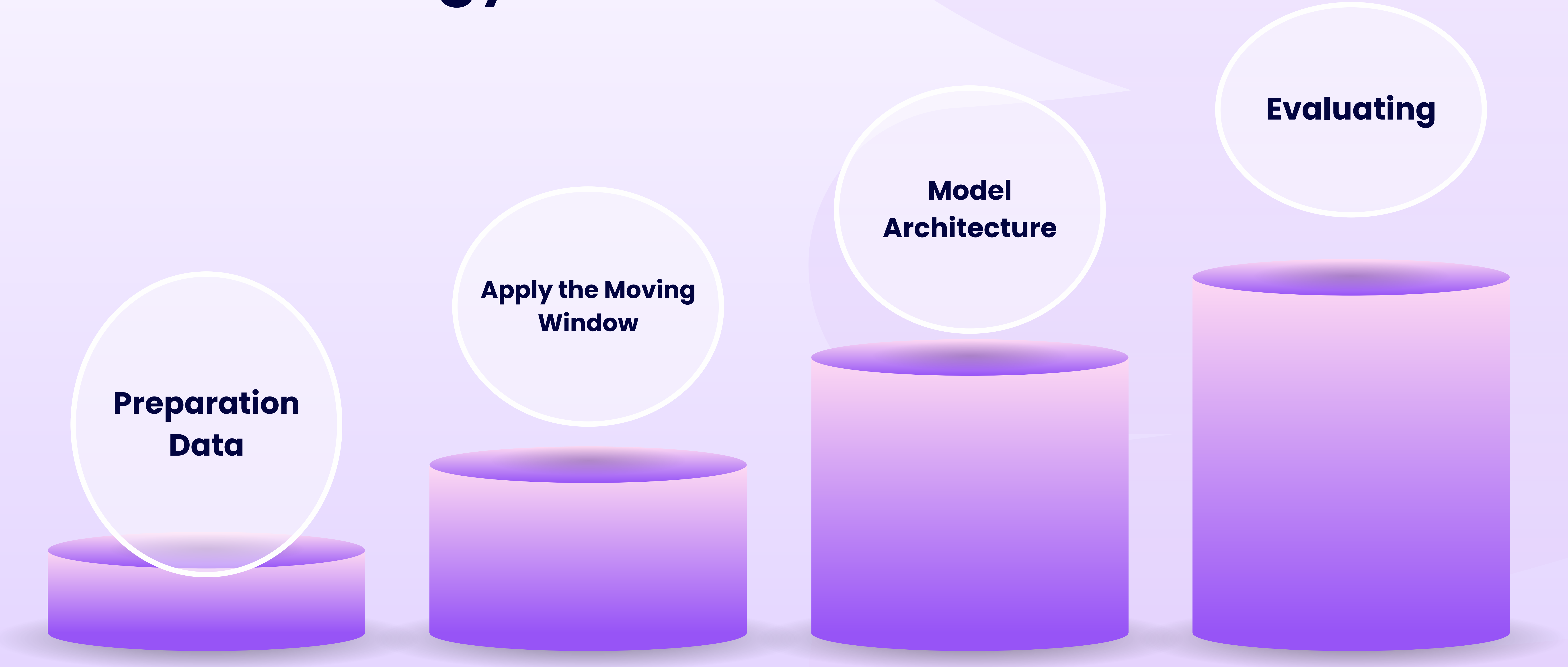
- BAZA Reem
- KARABAG Ata
- SÜSLÜ Ali Emre

Objective:

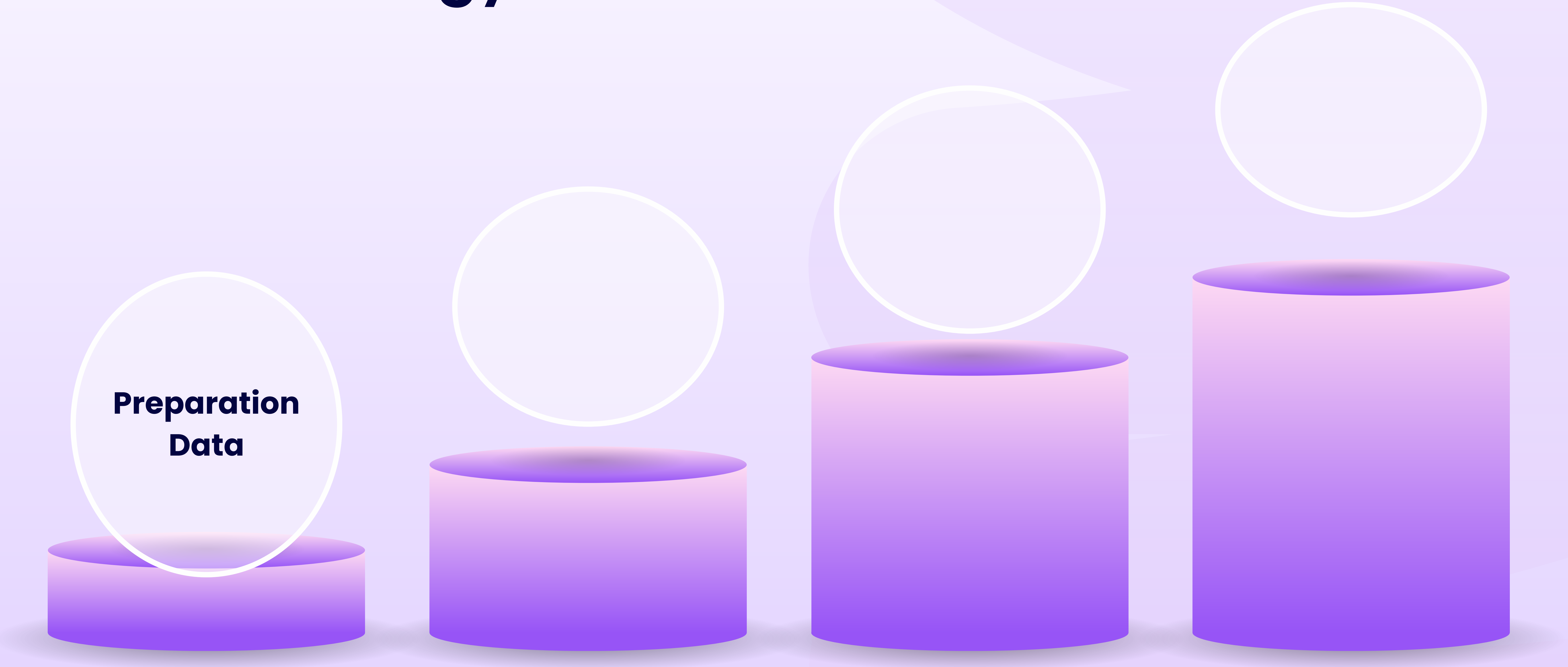
The goal of this project is to develop a deep learning model capable of predicting future stock prices for major companies based on historical market data

Our dataset comprises five years (2018—2023) of daily stock market records for 10 companies that are part of top 500 global companies

Methodology



Methodology



Methodology

Load & Clean the Data

Preparation Data

Methodology

Load & Clean the Data

Preprocess Time-Series

Preparation Data

Methodology

Preparation Data

- Load & Clean the Data
- Preprocess Time-Series
- Filter Target Companies

Methodology

Preparation Data

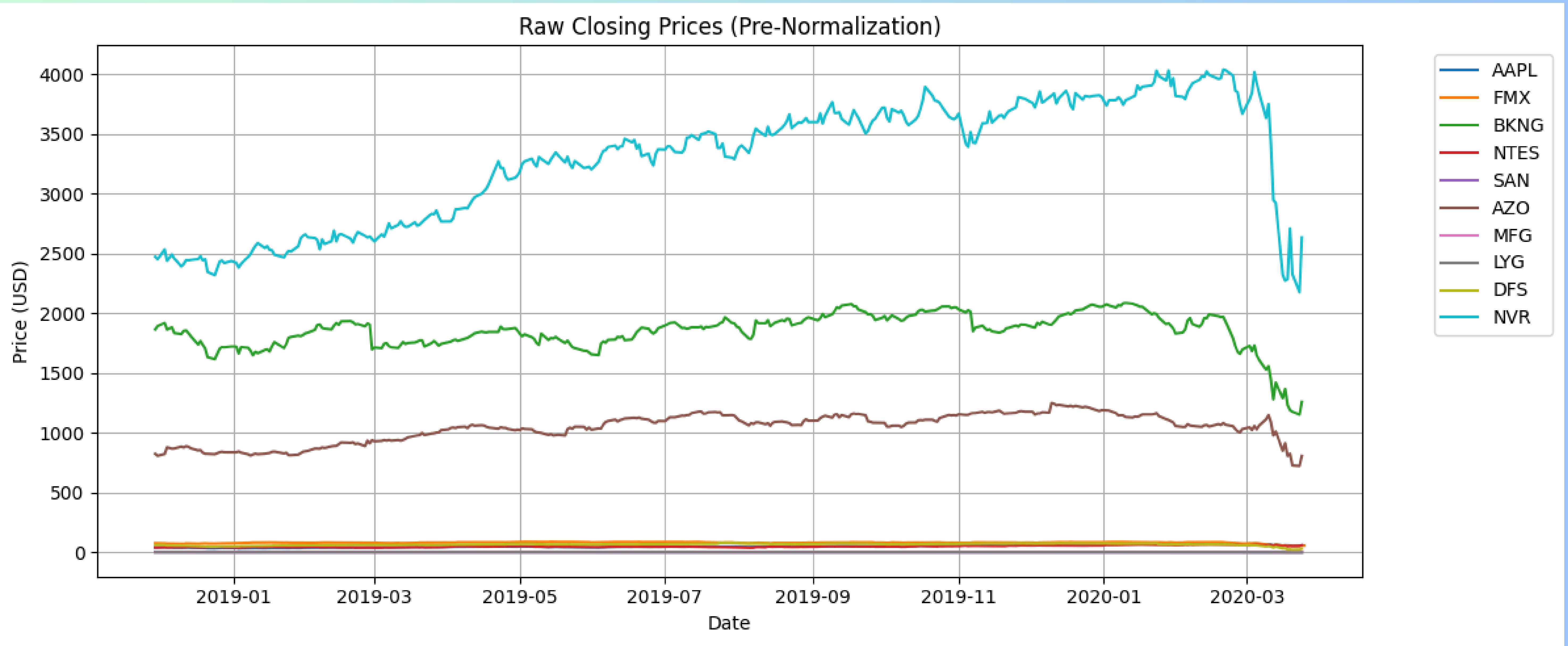
Load & Clean the Data

Preprocess Time-Series

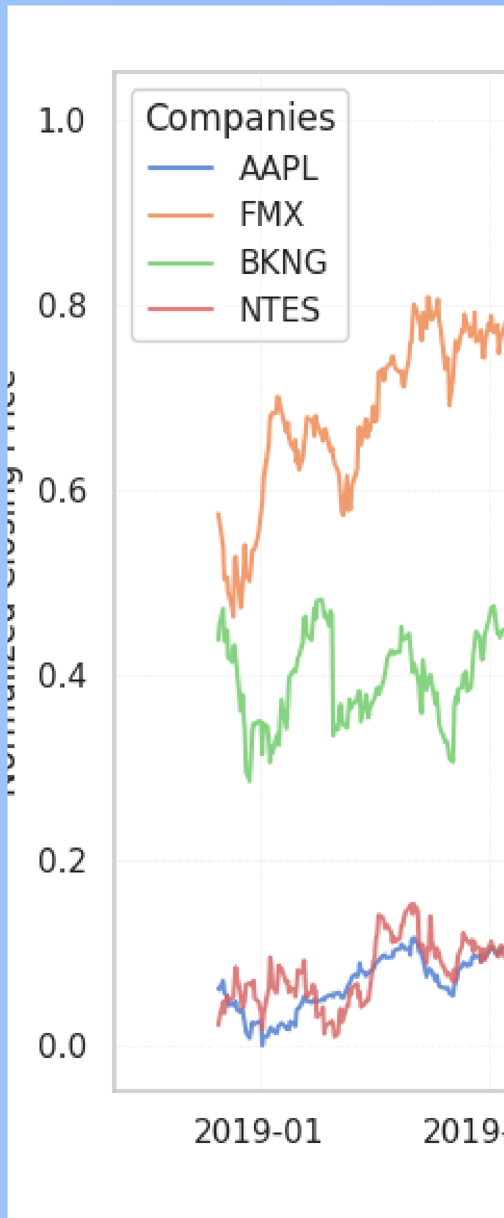
Filter Target Companies

Data Splitting and Normalization

Methodology

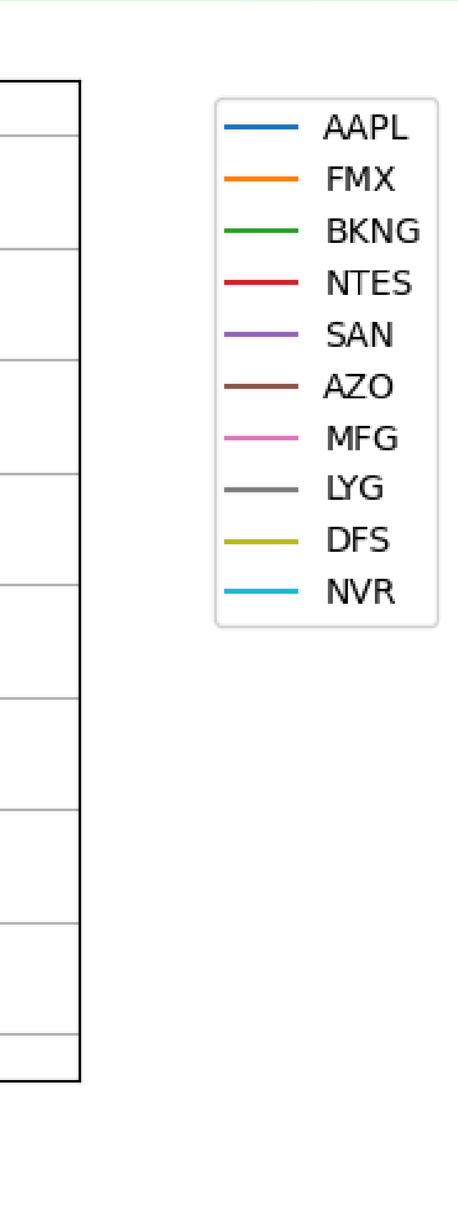


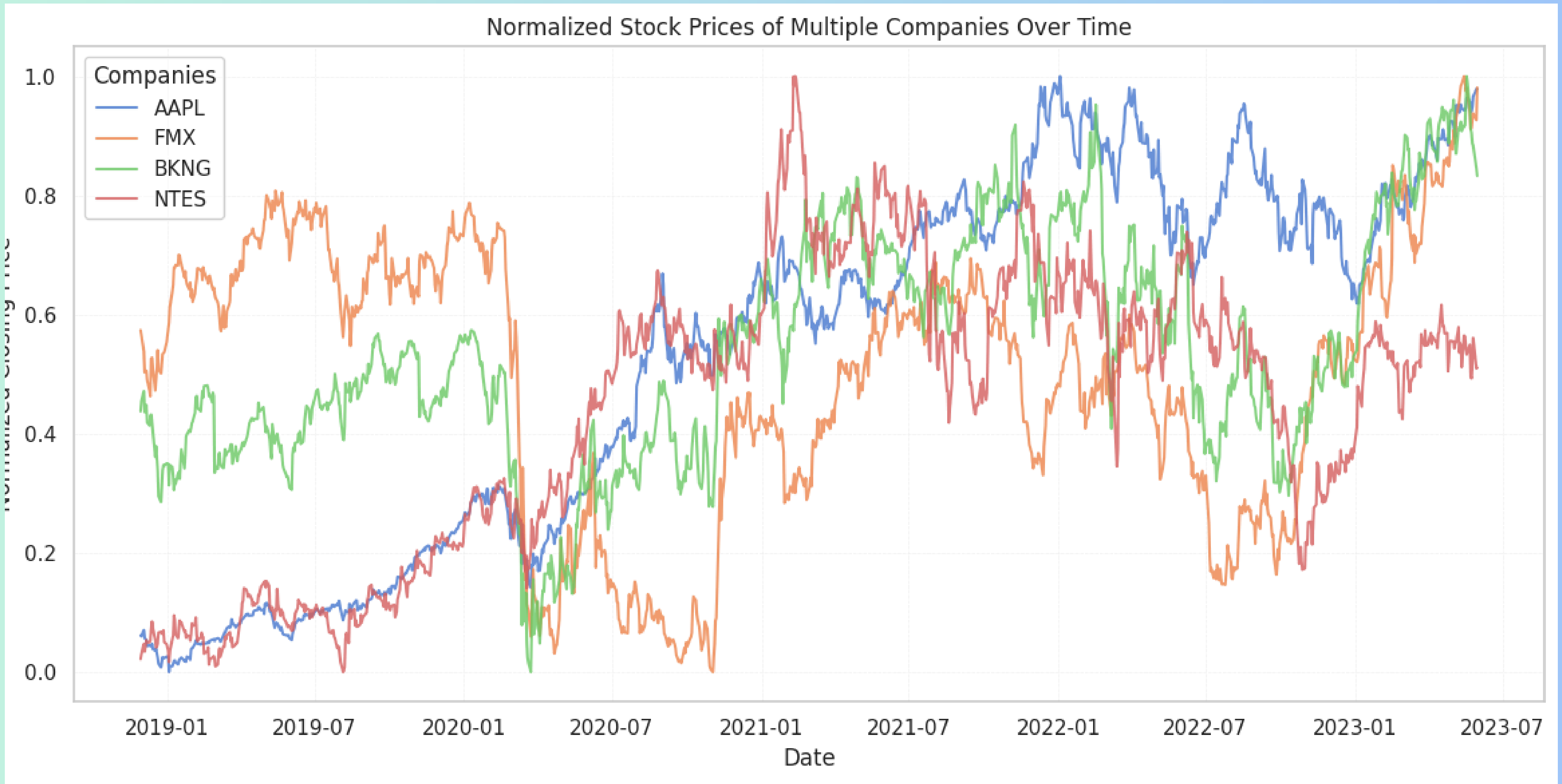
before normalizing



after r

Methodology

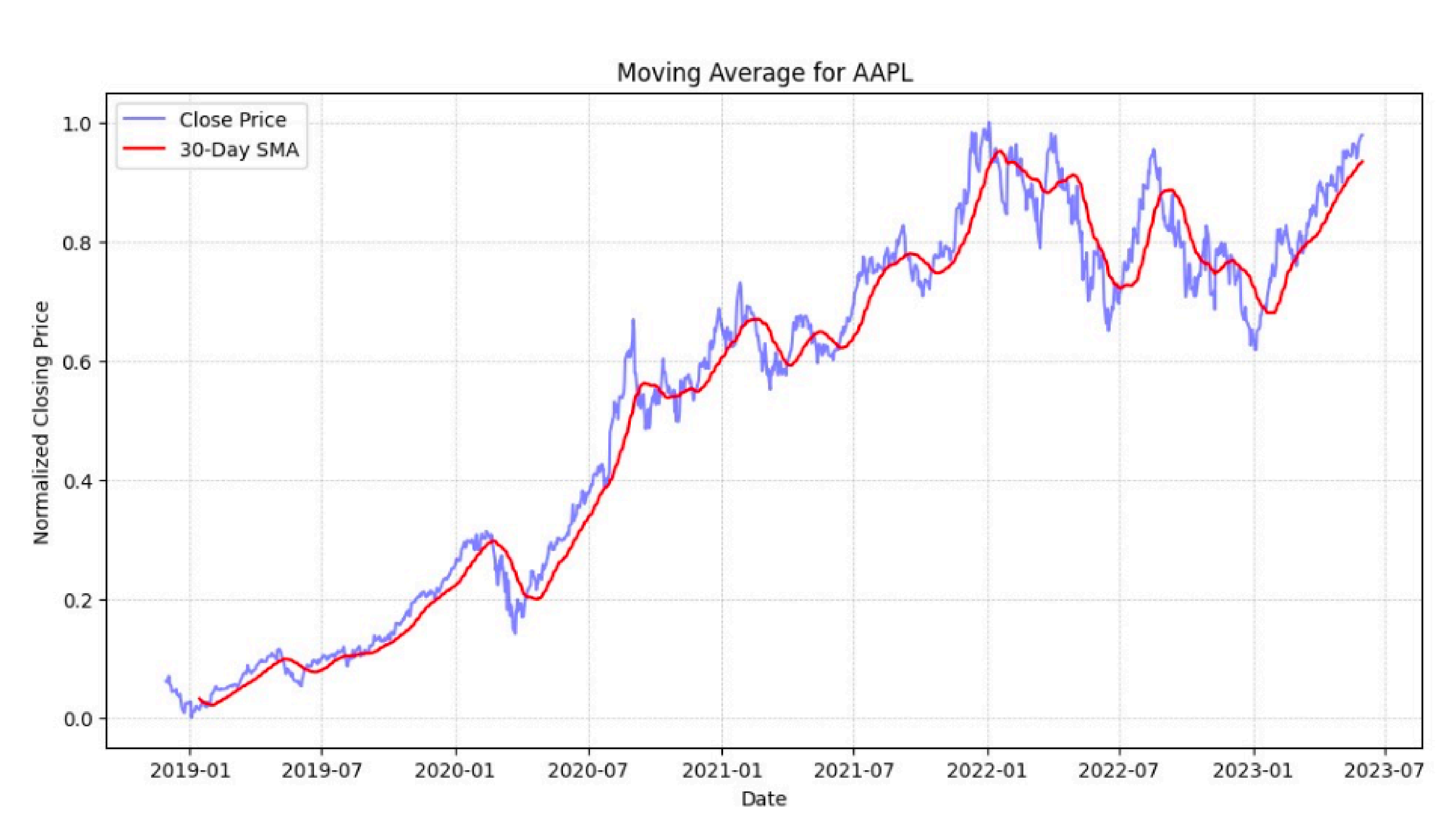




ng

after normalizing

Methodology



Stock Price is going up → The red line (SMA) trends upward, confirming a long-term uptrend.
Stock Price is declining → The red line trends downward, indicating a bearish trend.

This helps traders and investors make decisions like:
✅ Buying when the stock price crosses above the moving average.
✅ Selling when the stock price crosses below the moving average.

Methodology

Preparation Data

Apply the Moving Window

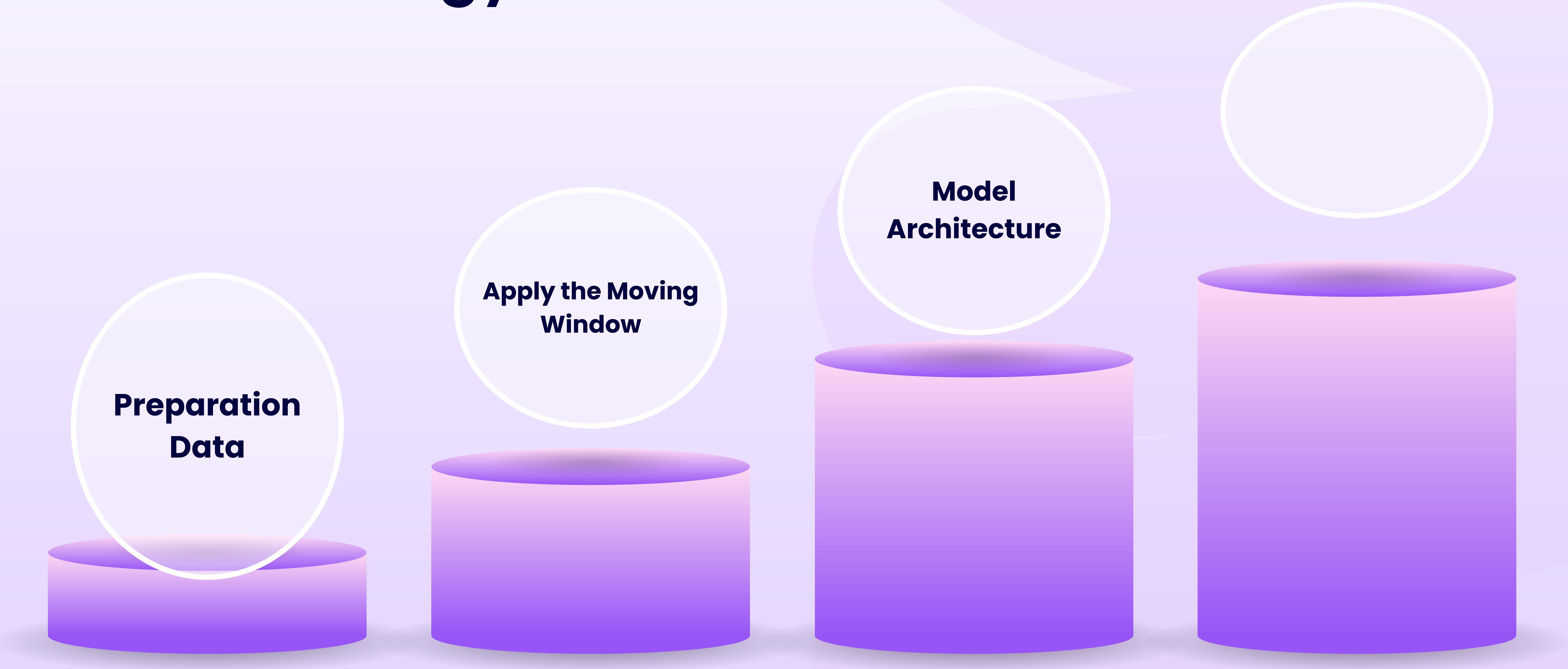
Methodology

To allow the model to learn from historical trends.

Instead of treating each data point independently, the model is trained to use a sequence of past values to predict future values.

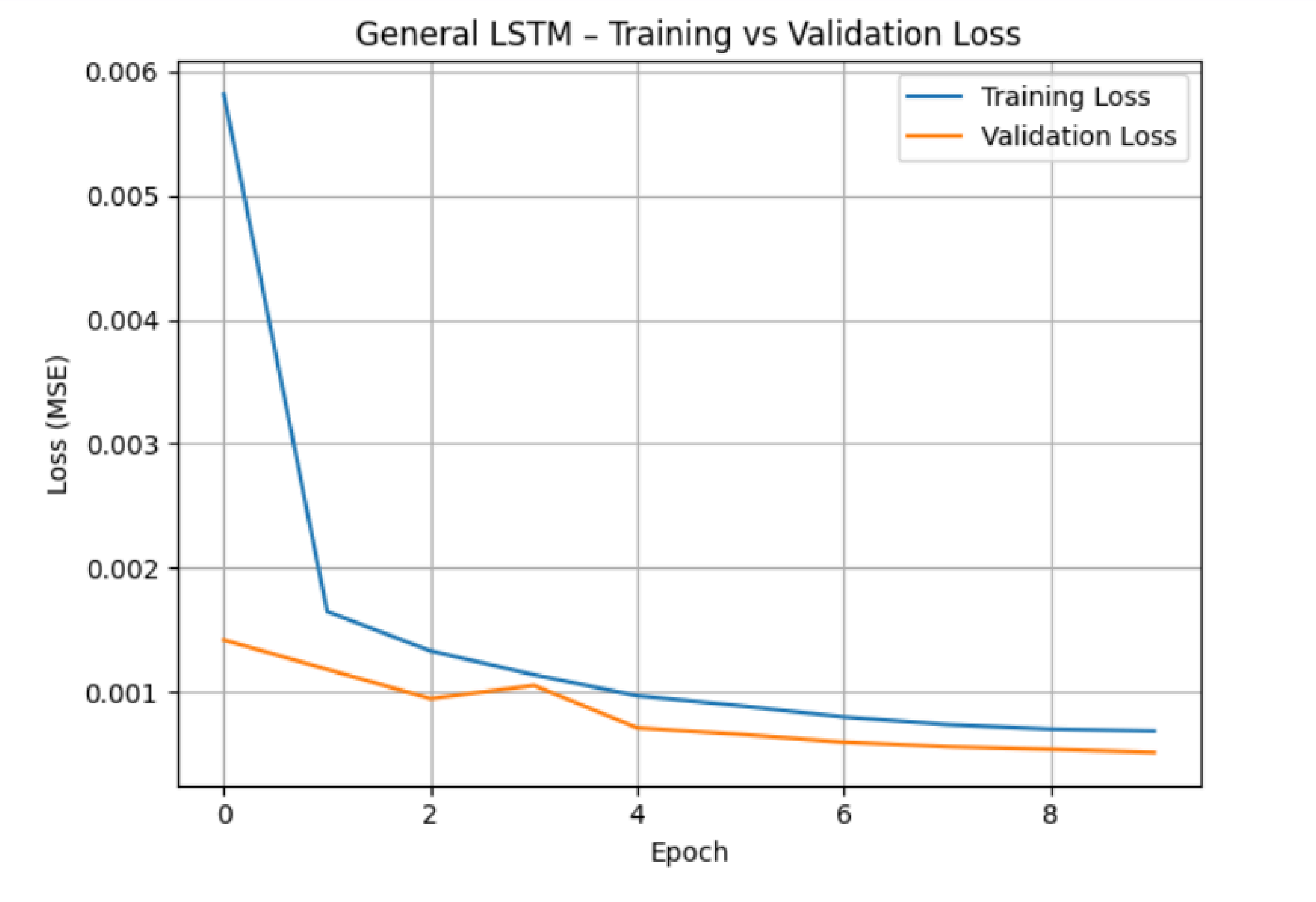
We use 60-day sliding window, served as input , to predict the 61st day's .

Methodology



LSTM model

trained on a combined dataset from all 10 companies



Both curves decrease smoothly, which indicates that the model is learning effectively and generalizing well to unseen data.

Importantly, there are no signs of overfitting, as the validation loss consistently follows the training loss throughout the training.

Methodology

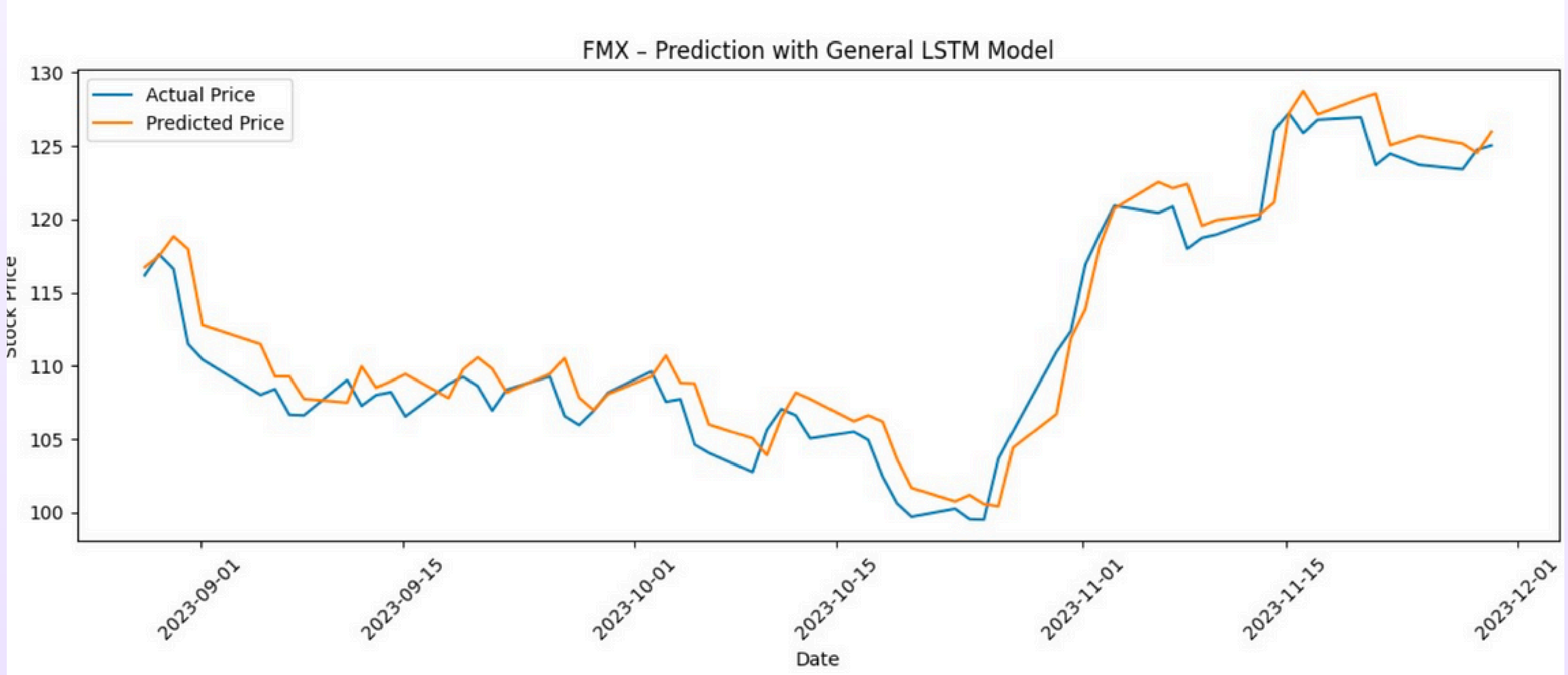
Preparation Data

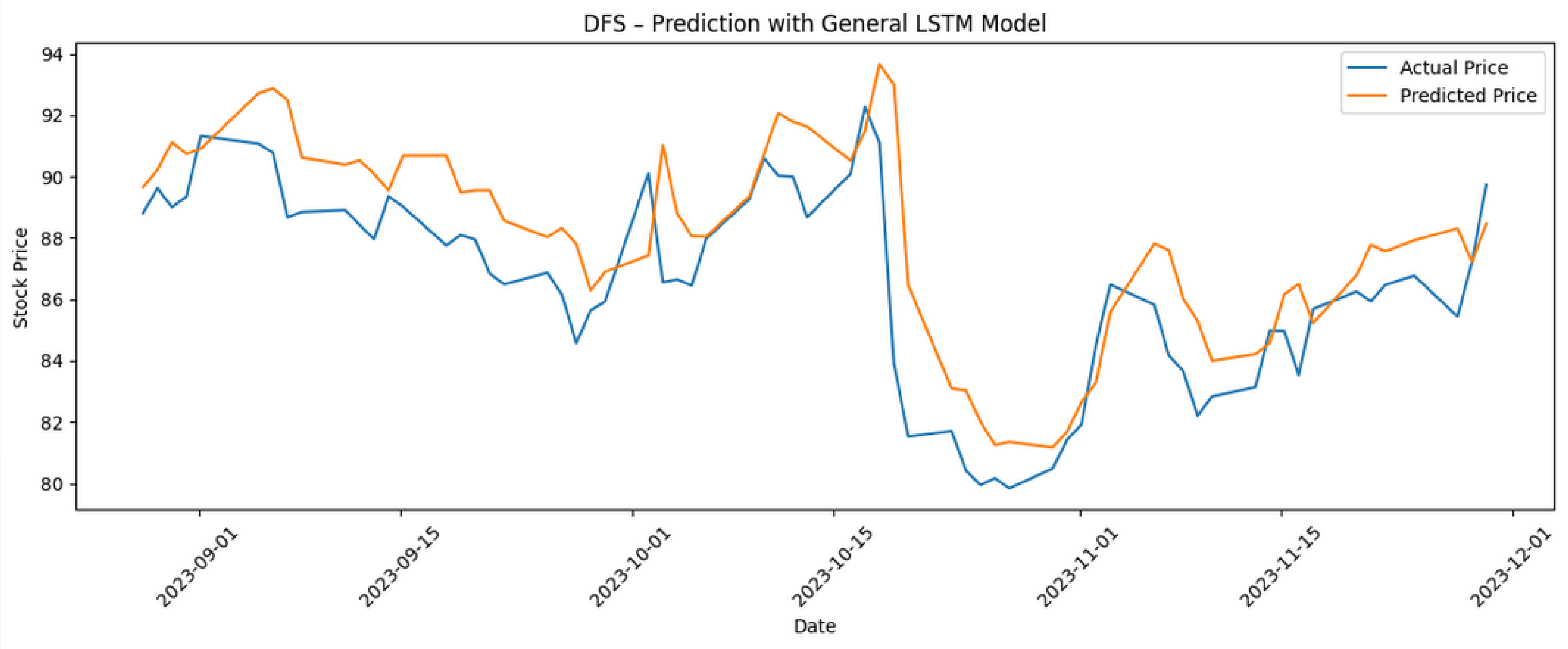
Apply the Moving Window

Model Architecture

Evaluating LSTM

EVALUATION:





FMX COMPANY

MAE : 1.78

MSE : 5.20

RMSE: 2.28

R^2 0.9201

DFS COMPANY

MAE : 1.76

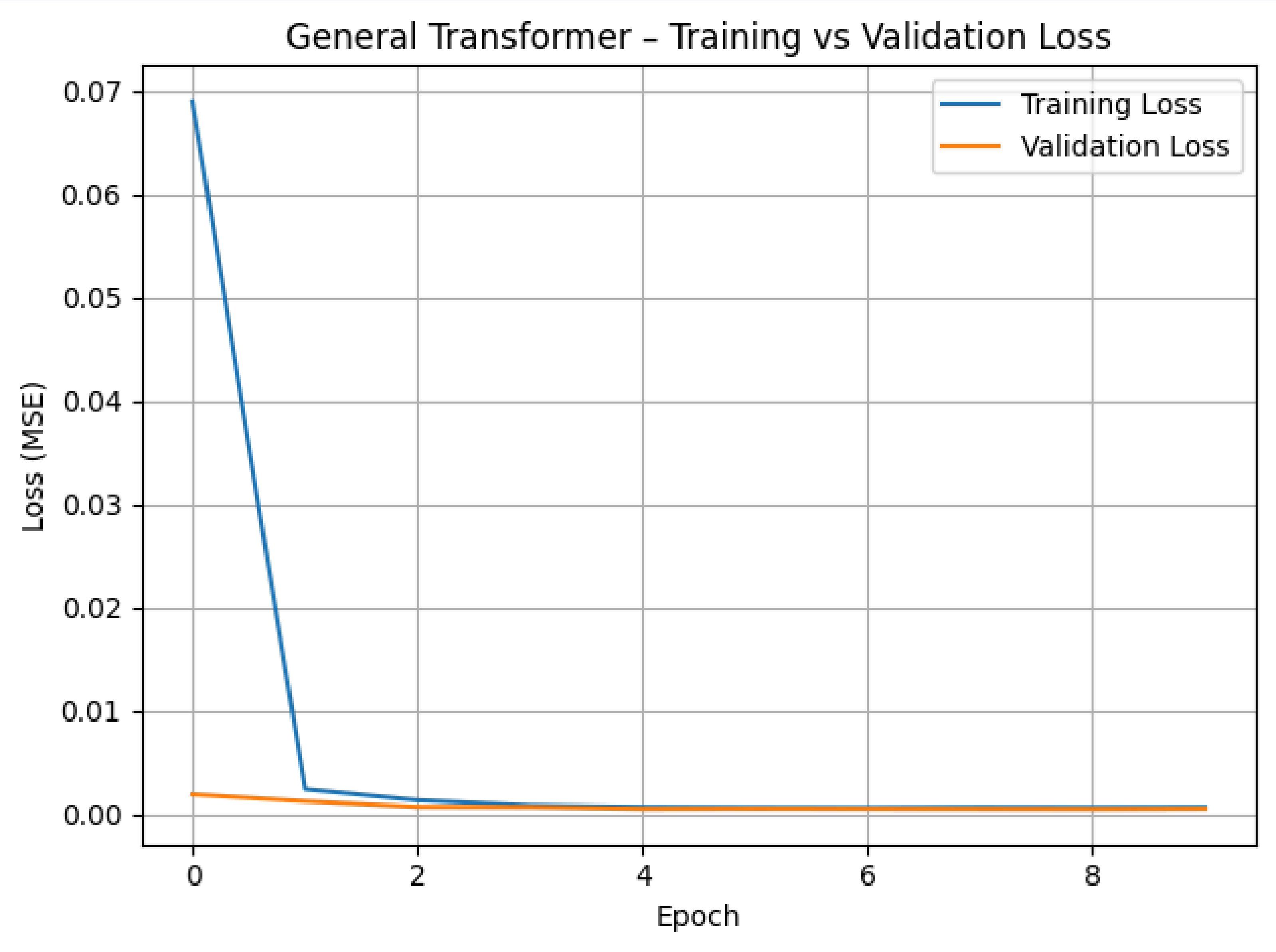
MSE : 5.05

RMSE: 2.25

R^2 : 0.4989

Transformer model

trained on a combined dataset from all 10 companies



The Transformer model converged extremely quickly — both training and validation loss dropped to near-zero within the first few epochs.

This suggests the model fits the data very well and generalizes without overfitting.

However, the fast convergence might also mean the model is very powerful or that the dataset has strong patterns the model easily learns

Methodology

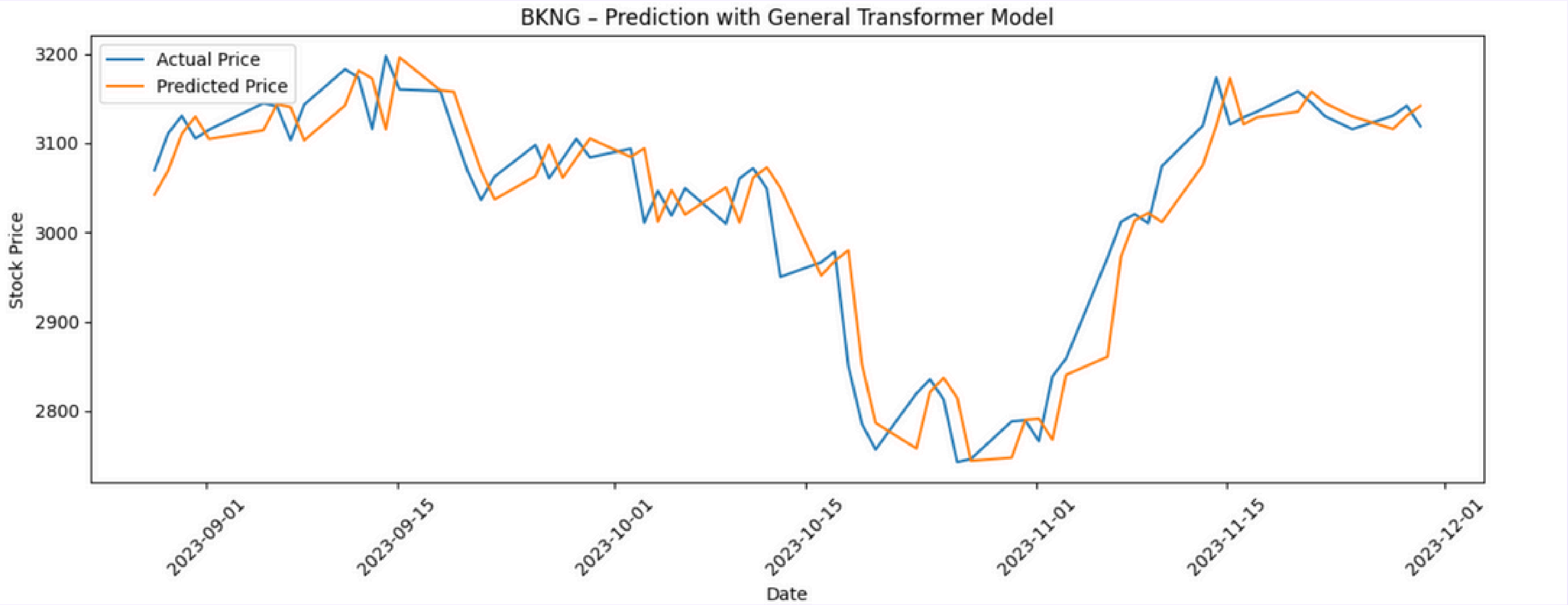
Preparation Data

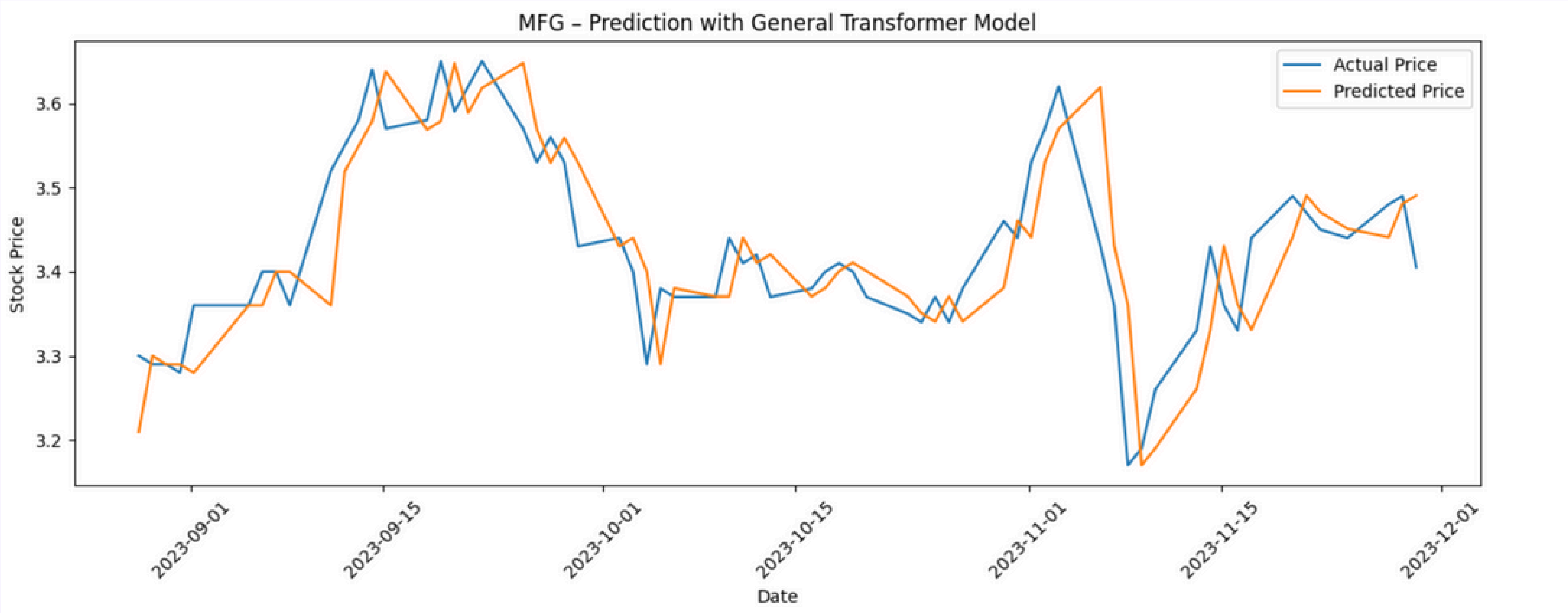
Apply the Moving Window

Model Architecture

Evaluating transformer

EVALUATION:





BKNG COMPANY

MAE : 33.9

MSE : 1.85

RMSE: 43

R^2 : 0.887

MFG COMPANY

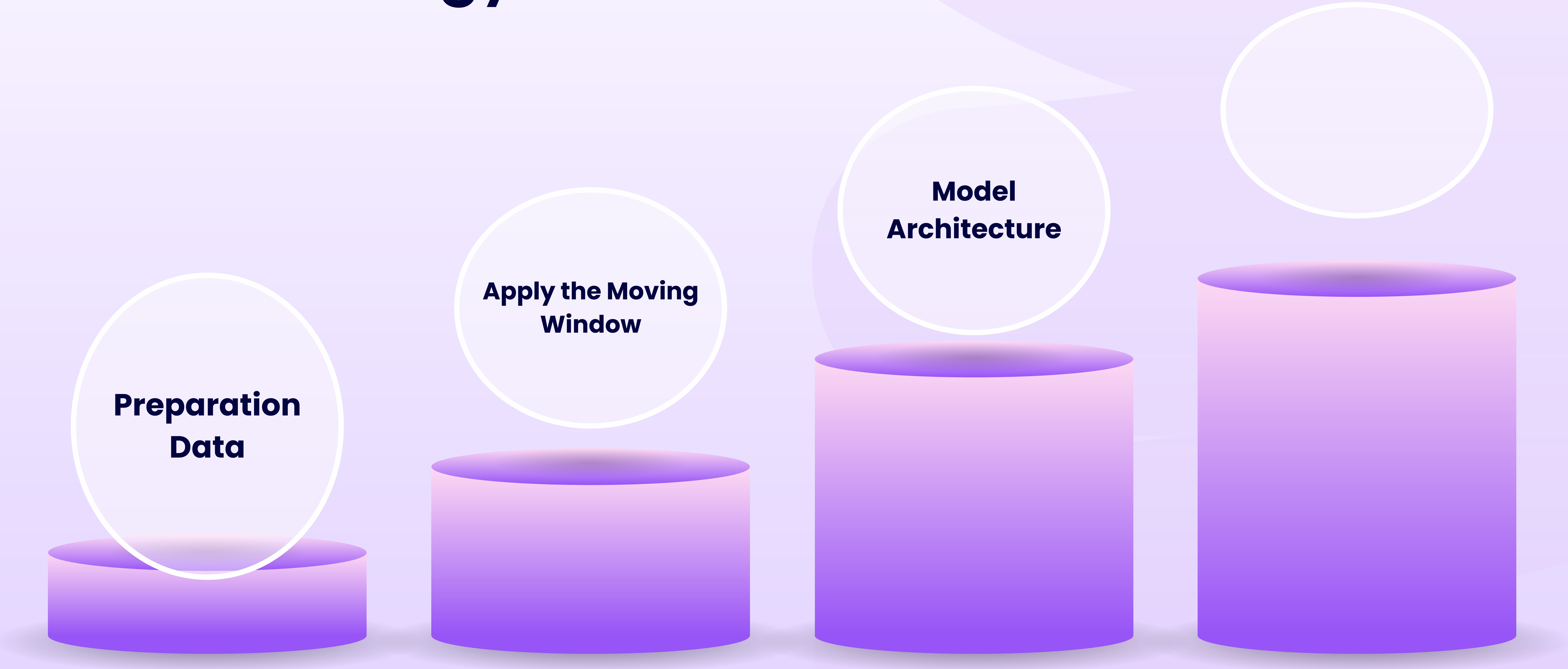
MAE : 0.05

MSE : 0.01

RMSE: 0.06

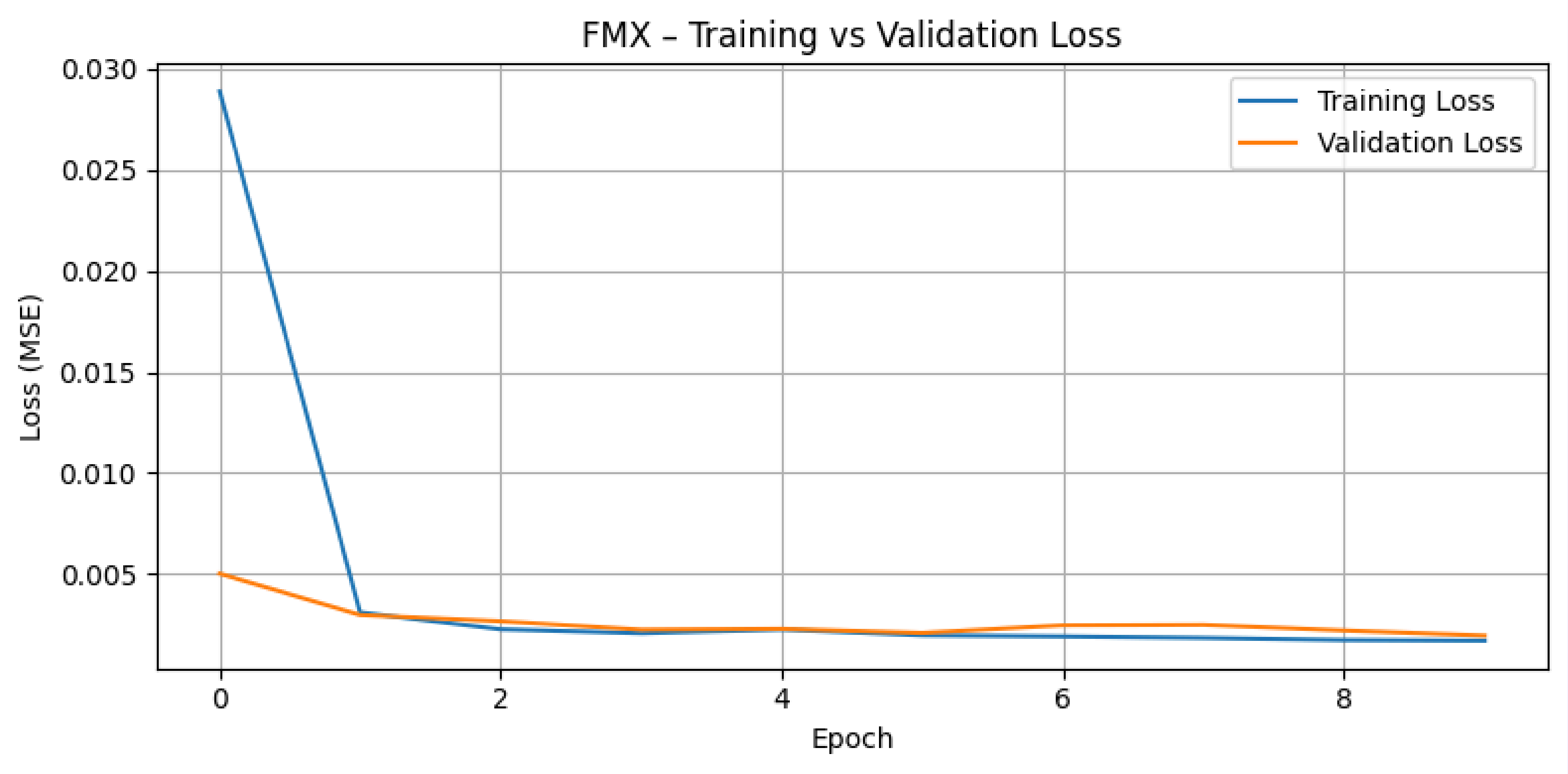
R^2 : 0.625

Methodology



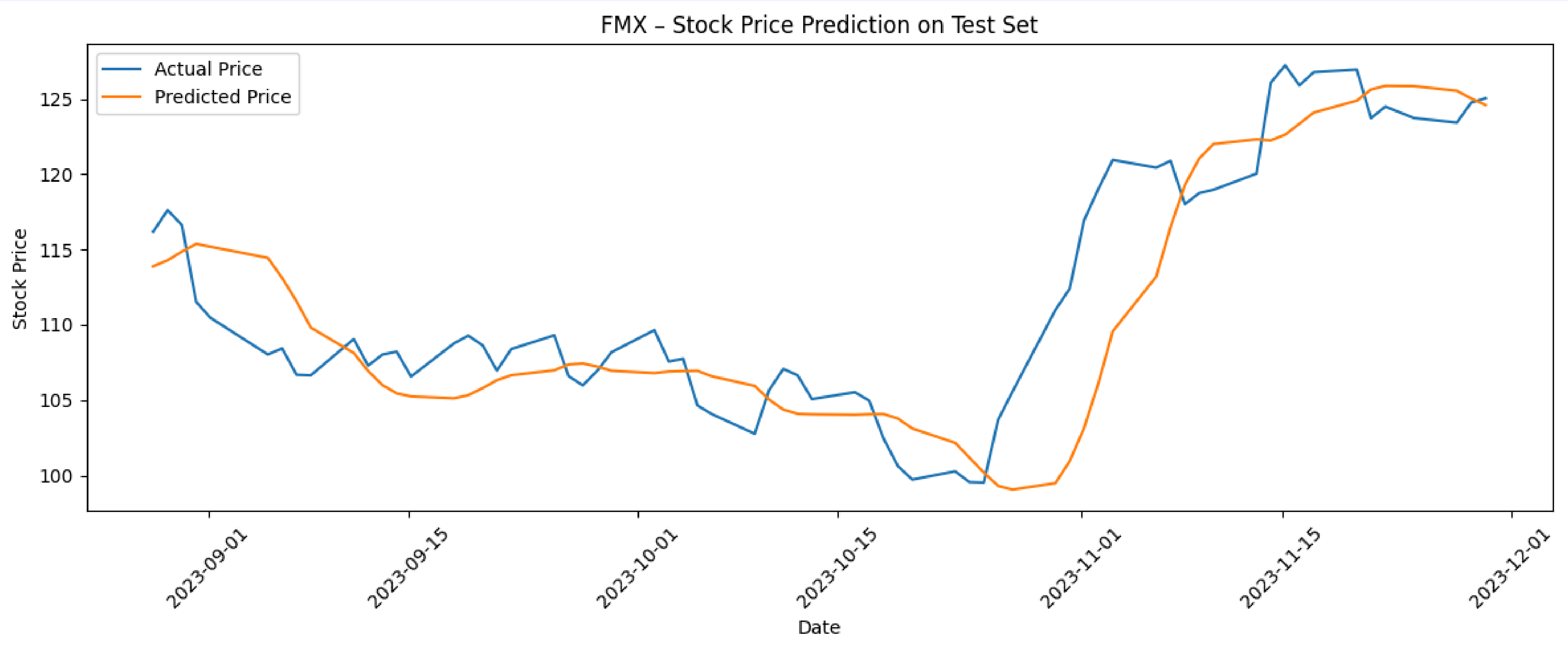
LSTM model

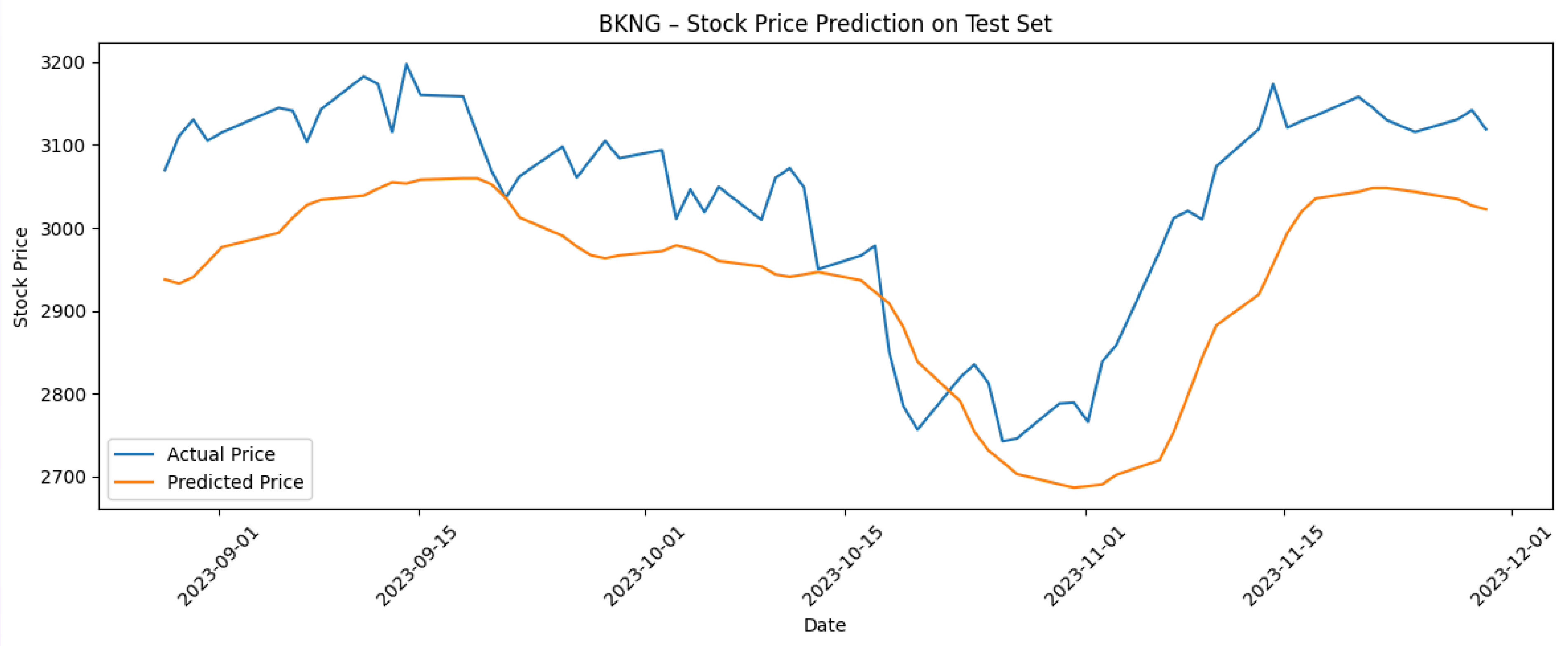
trained on a individual dataset for Each Company:



We trained individual LSTM models for each company to predict stock prices based on their own historical data. Each model takes the past 60 days of closing prices and learns temporal patterns unique to that company. This approach allows each LSTM to specialize in the behavior of a specific stock, improving accuracy for company-specific trends.

EVALUATION:





FMX COMPANY

MAE : 3.21

MSE : 19.25

RMSE: 4.39

R^2 : 0.69

BKNG COMPANY

MAE : 107.01

MSE : 14520.15

RMSE: 120.50

R^2 : 0.118

CONCLUSION:

we compared the average R^2 scores across all companies:

- LSTM model average R^2 score across all companies: 0.6971
- Transformer model average R^2 score across all companies: 0.8154
- Individual LSTM models average R^2 score: 0.3581

Overall, we conclude that the Transformer model is the most effective for this stock prediction task
But what can we do for better results?