

# ***Recurrent Neural Networks Stock Price Prediction***

presented by  
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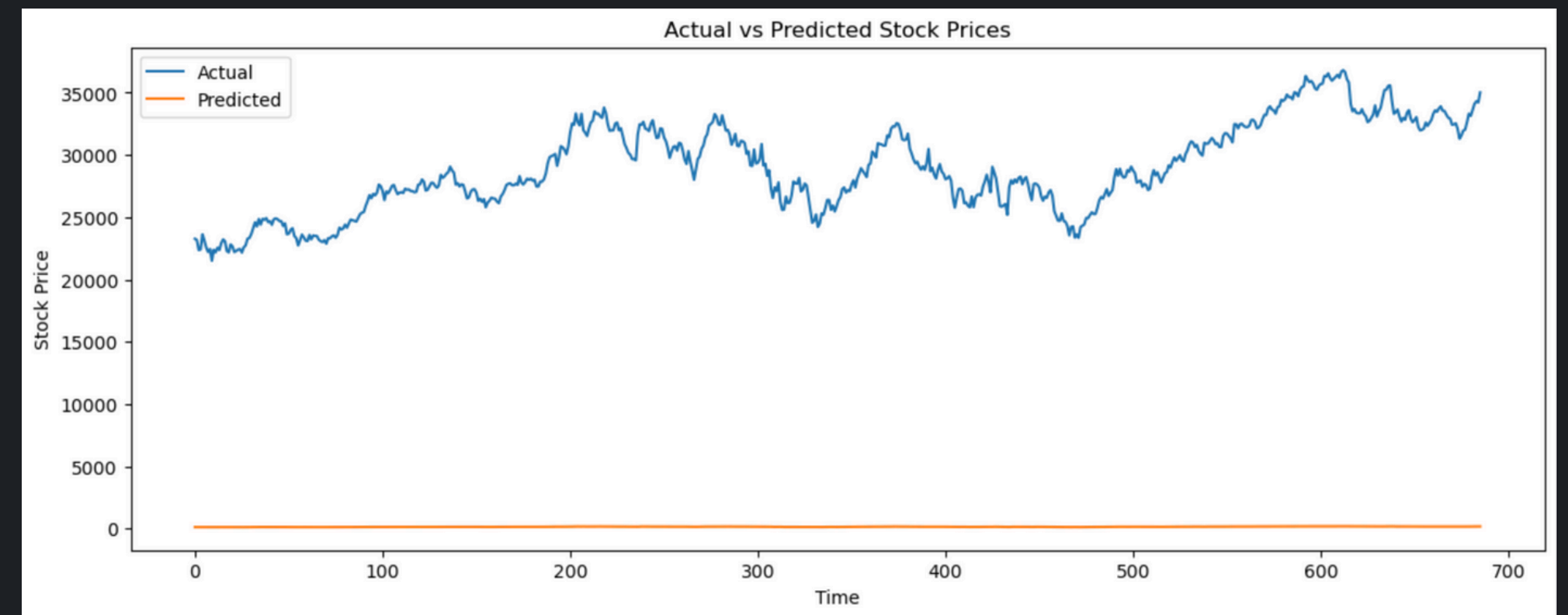
# Project Overview

- Goal: Compare LSTM and GRU for predicting AAPL stock prices
- Investigate how additional factors (Volume, OHLC) impact prediction performance
- Experiment with activation functions in GRU (ReLU, LeakyReLU, ELU)
- Evaluate models based on RMSE and behavior during training



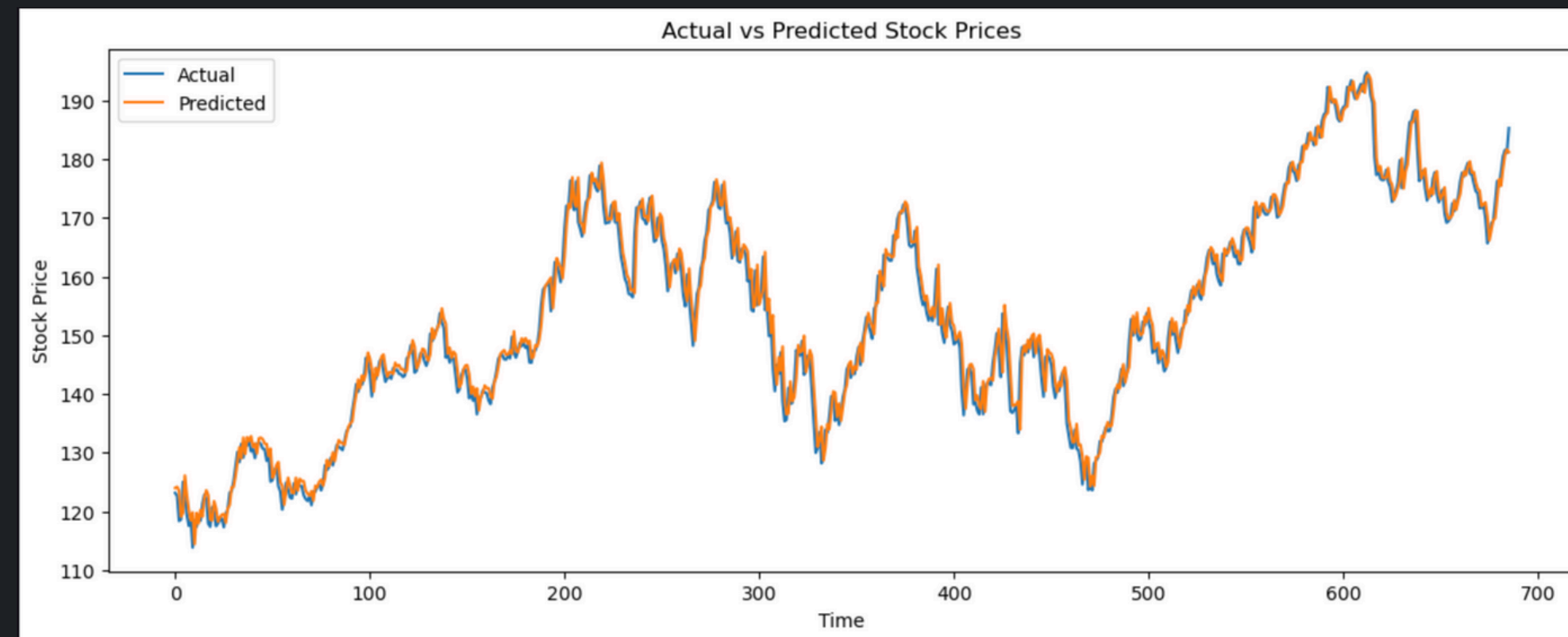


- LSTM struggled → produced flat and non-informative predictions
- Close-only dataset too limited → LSTM failed to converge meaningfully
- GRU handled limited data better → followed price trends, though accuracy was modest
- Reinforced need for more context (features) for models like LSTM

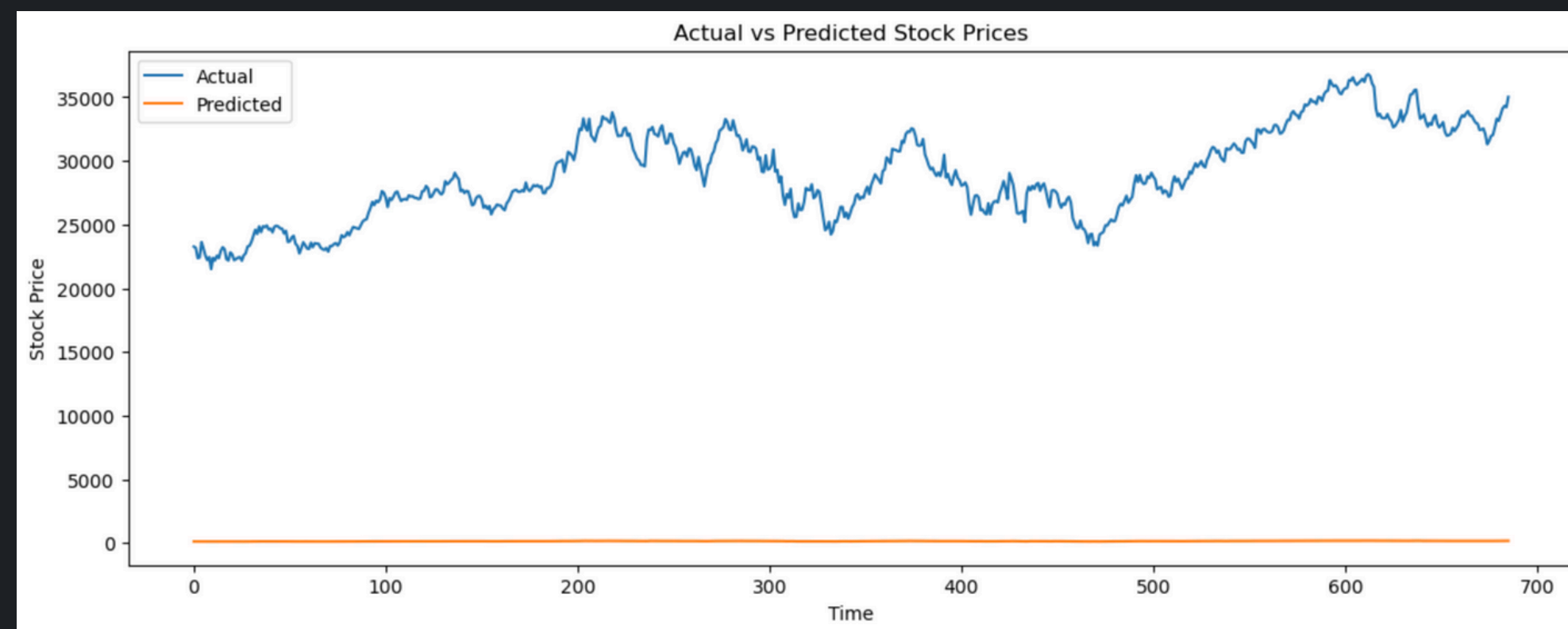


# Model Observations

*LMST (Close only)*



*GRU (Close only)*



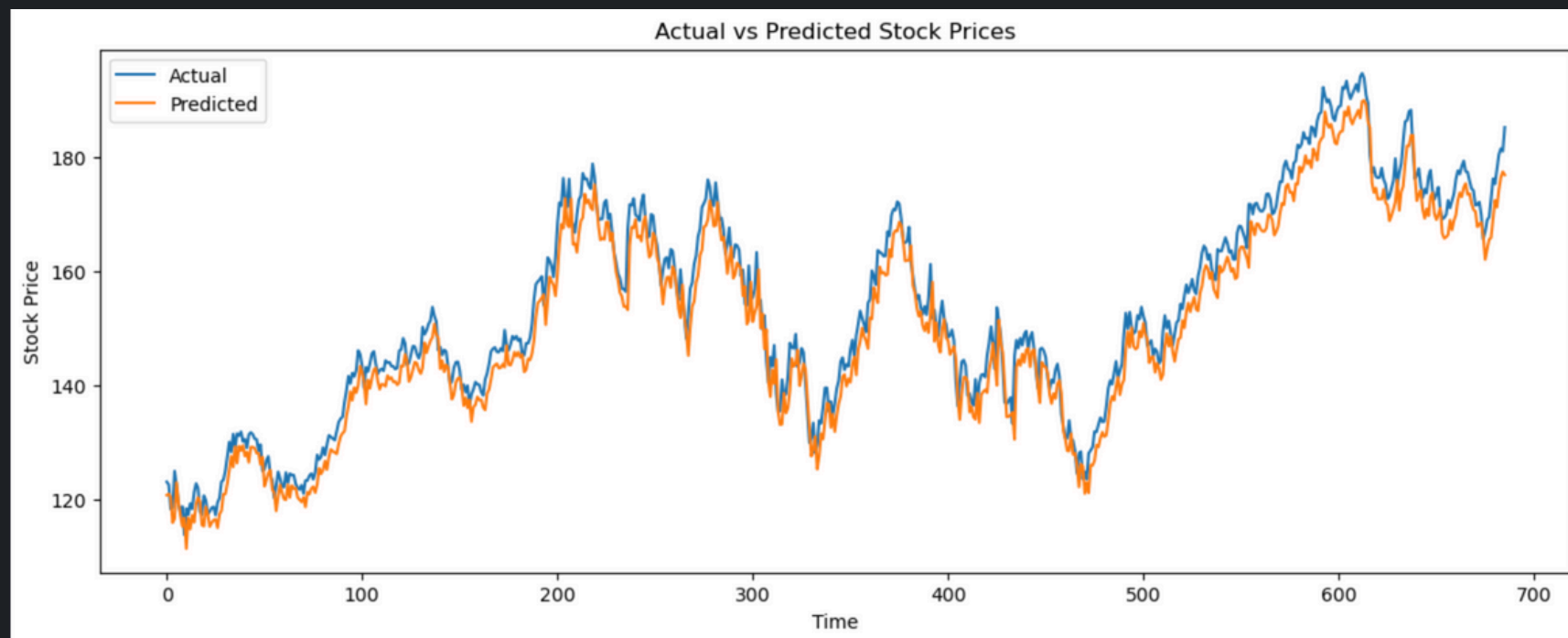
*LMST (Close only)*

**Model  
Observations**

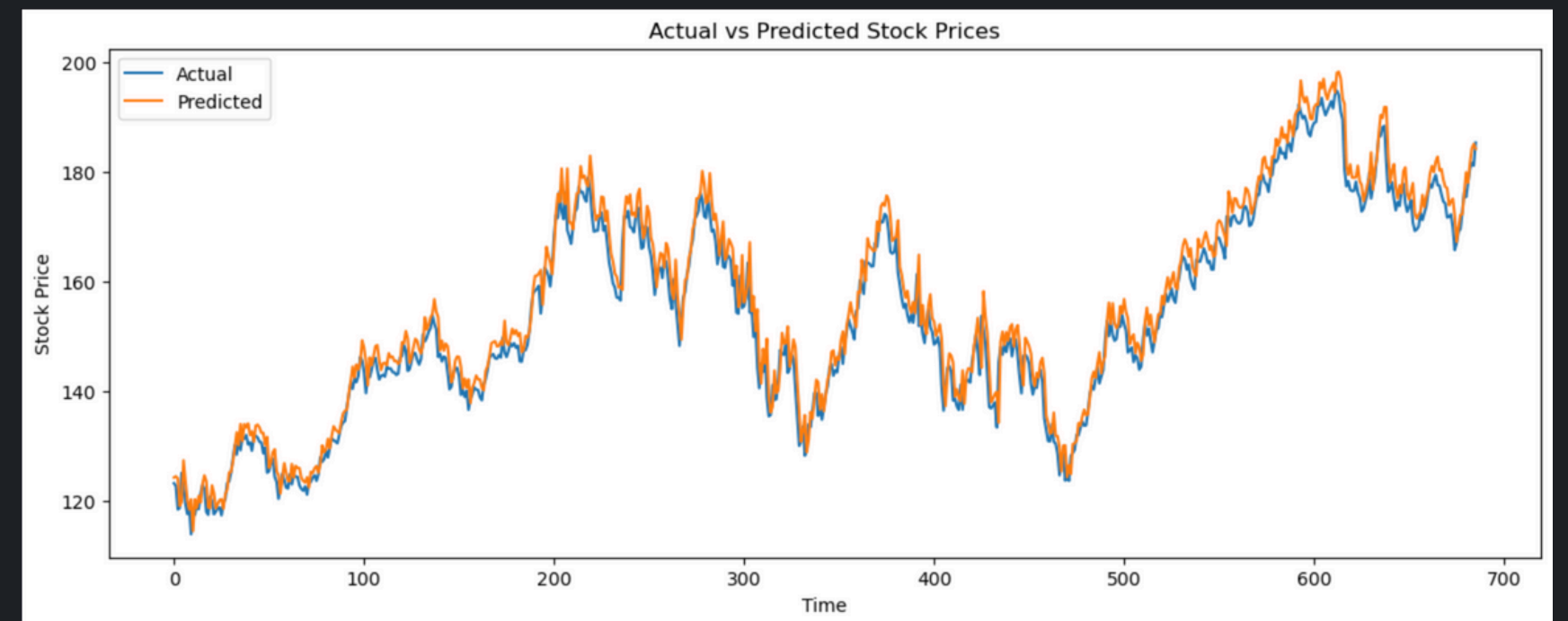


# Adding Volume

- ✿ Adding Volume improved prediction quality for both models
- ✿ GRU became much more responsive and closed the performance gap
- ✿ LSTM also performed very well, possibly matching or slightly outperforming GRU at this stage.



***GRU (Close + Volume)***



***LSMT (Close + Volume)***

# OHLC + Volume → GRU Takes the Lead



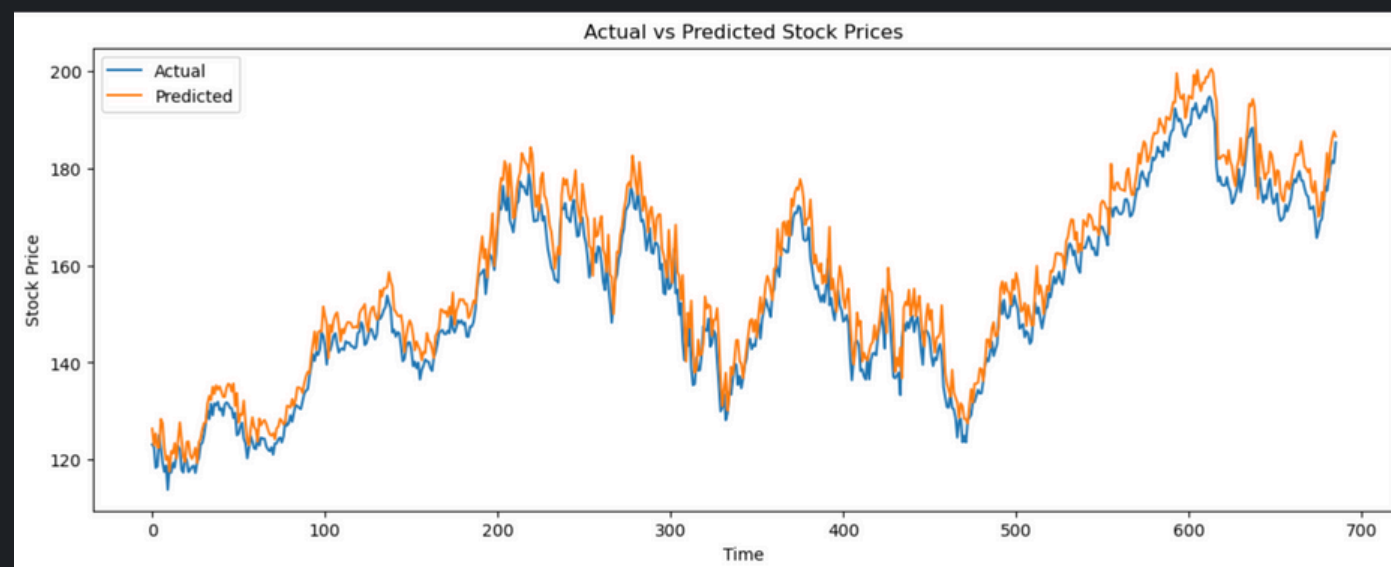
Adding OHLC introduced richer feature set → GRU handled this complexity better



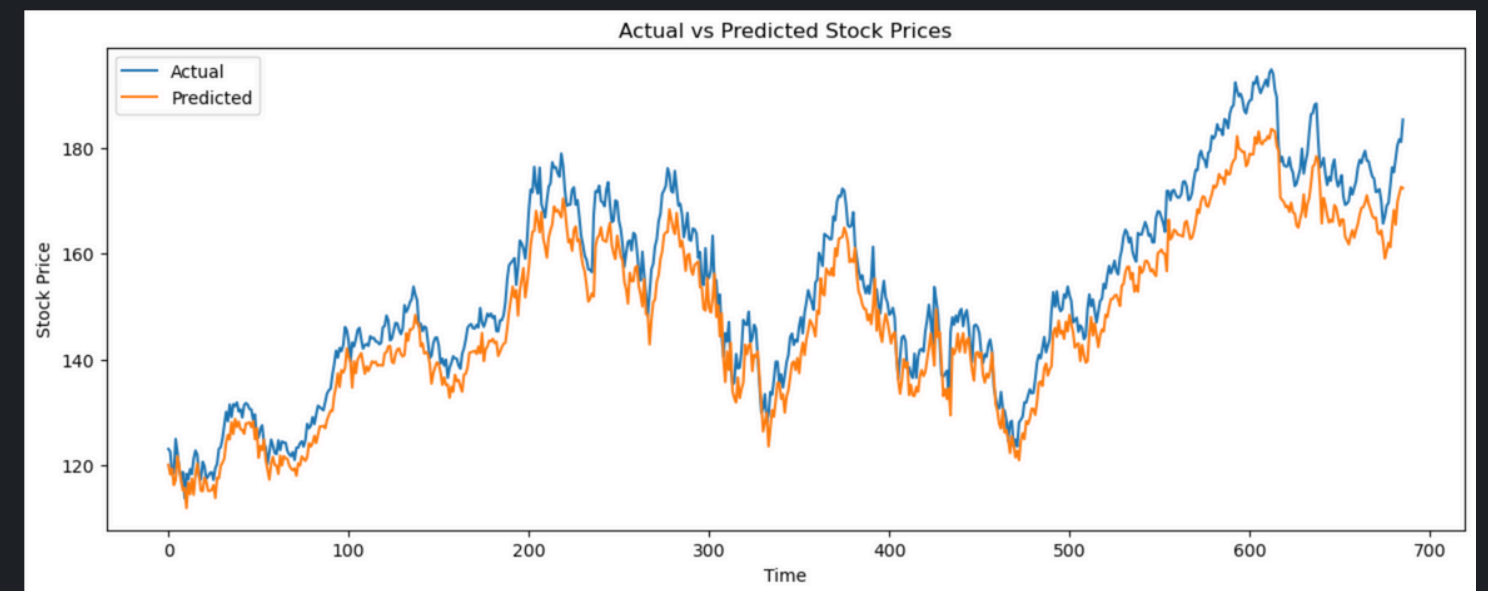
Adding OHLC introduced richer feature set → GRU handled this complexity better



LSTM was still competitive, but GRU showed its scaling advantage



*LSTM(Volume + OHLC)*



*GRU(Volume + OHLC)*



# ***GRU Activation Function Experiments***

- ✿ **ReLU**

Tracked overall trend but consistently underpredicted stock prices.

- ✿ **LeakyReLU**

Slightly improved tracking over ReLU but still fell short of actual prices.

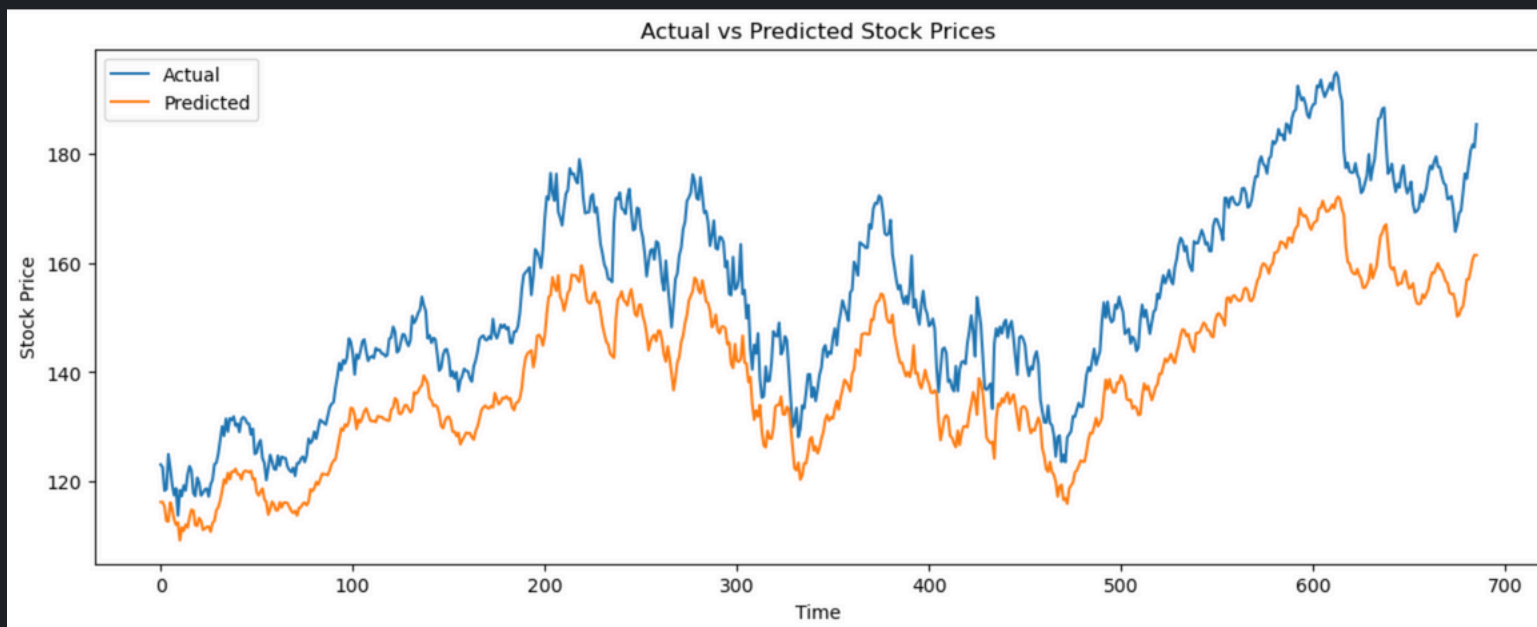
- ✿ **ELU**

Best performer, closely following actual prices with smaller gaps.

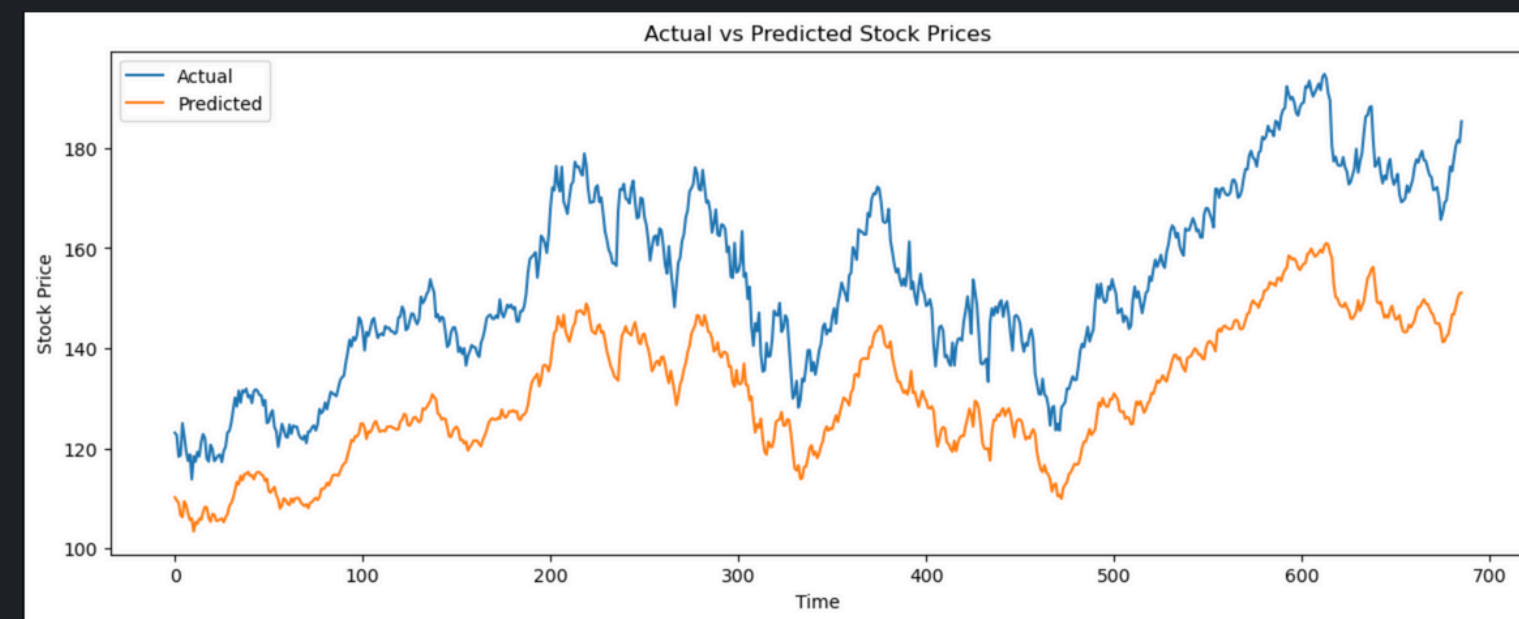
- ✿ **Conclusion →**

ELU activation offered the most accurate and stable predictions overall.

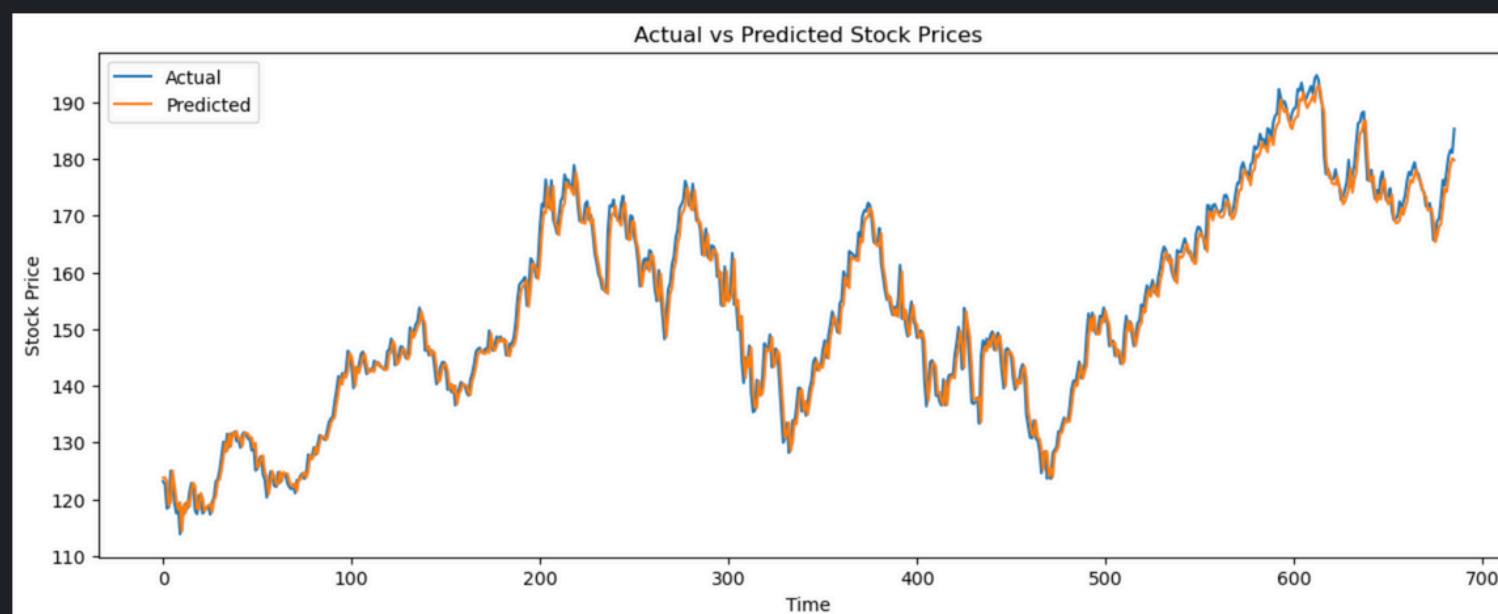




ReLU



LeakyReLU



ELU

# GRU Activation Function Experiments



# Challenges *Encountered*

- Input shape management became more difficult as features were added
- LSTM's inability to handle Close-only highlighted risks of underfitting with limited data
- Activation experiments → small tweaks had large effects on training stability
- psutil + TensorBoard helped monitor efficiency during experiments



## ✿ LSTM

better suited for more complex patterns, but requires sufficient input data

## ✿ GRU

more flexible and adaptable, especially as input complexity increases

## ✿ LeakyReLU

best activation function tested → stable, fast, and consistent

# *Key Insights and Takeaways*

✿ Feature selection was critical → more data helped, but only when used thoughtfully



# *Future Directions*



- ✿ Test models on other stocks for generalization
- ✿ Add external market indicators (ex: sentiment analysis, macroeconomic signals)
- ✿ Explore alternative architectures like Transformers for further improvements



# *Final Reflection and Questions*

- *Subtle, but important differences emerged across experiments*
- *LSTM and GRU both viable, but GRU proved more flexible overall*
- *Future modeling success depends on carefully balancing architecture, features, and tuning*

# Thank you!

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