DAILY STOCK PRICE PREDICTOR

PREDICTING FUTURE STOCK PRICES USING TIME-SERIES DEEP LEARNING MODELS

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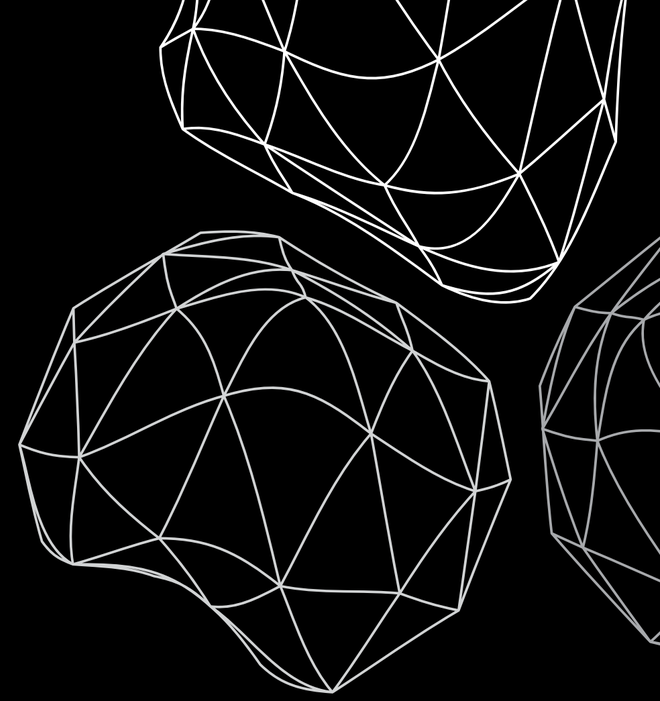
PROBLEM STATEMENT

Stock price movements are highly volatile and difficult to predict using traditional statistical models.

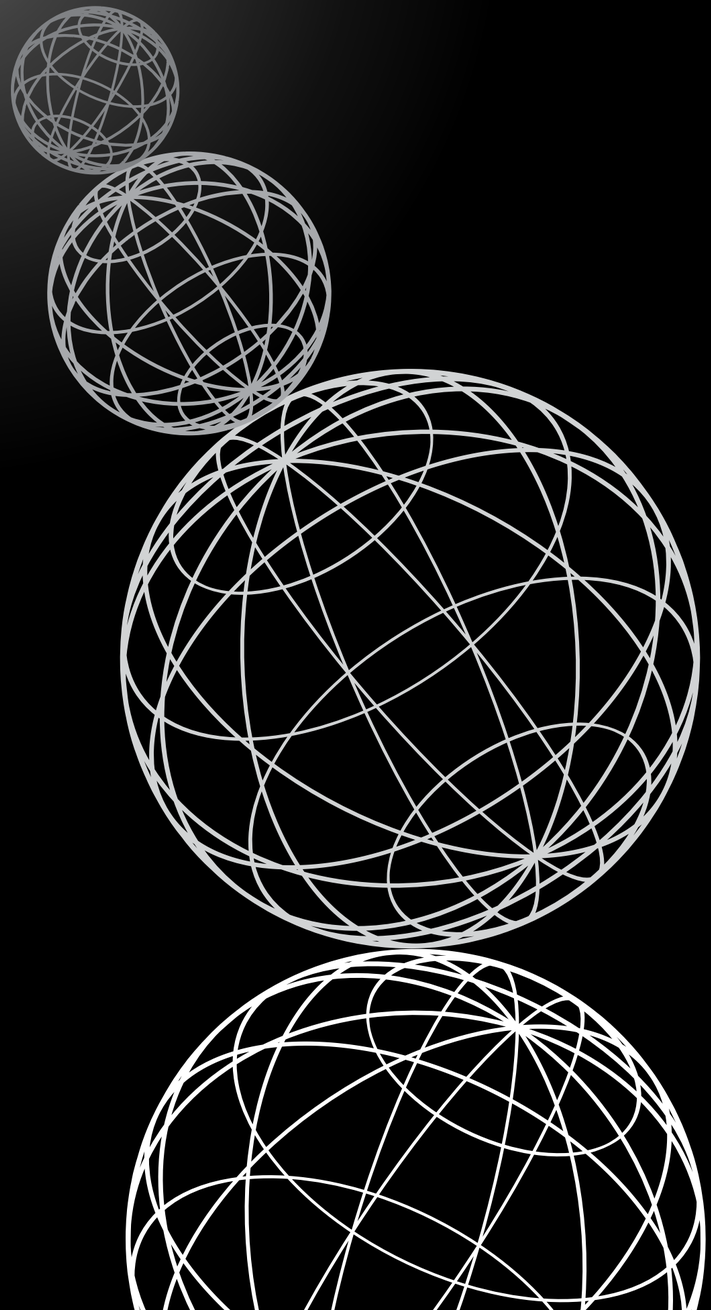
CHALLENGES

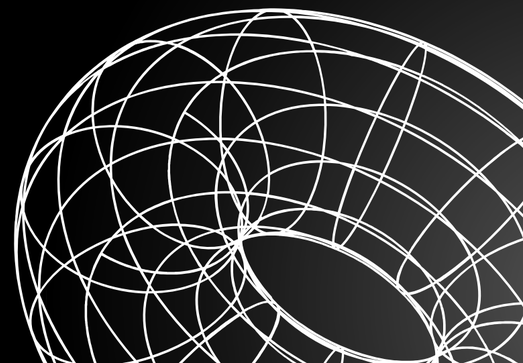
High noise in financial data
Dependency on multiple factors (news, sector, market trends)
Limited availability of high-frequency data



CORE IDEA

To develop an ML model that predicts future stock prices using past data patterns — helping investors make smarter, faster, and more accurate financial decisions



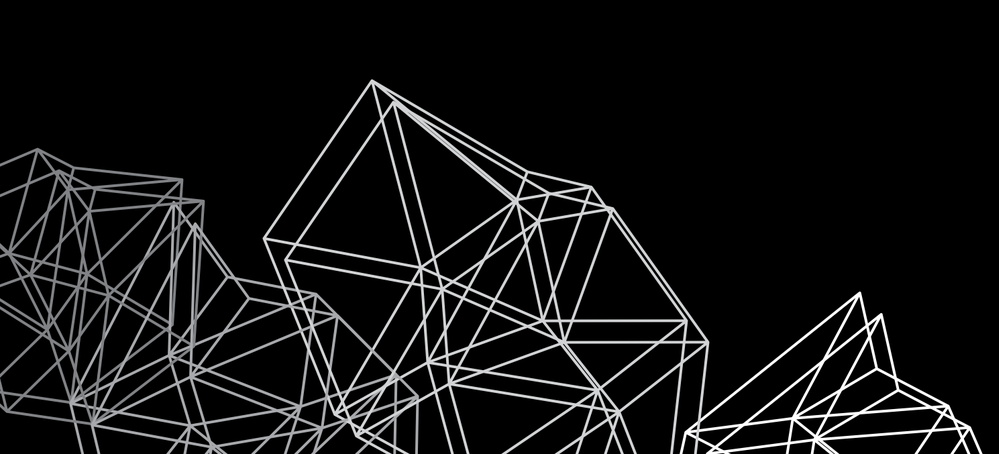


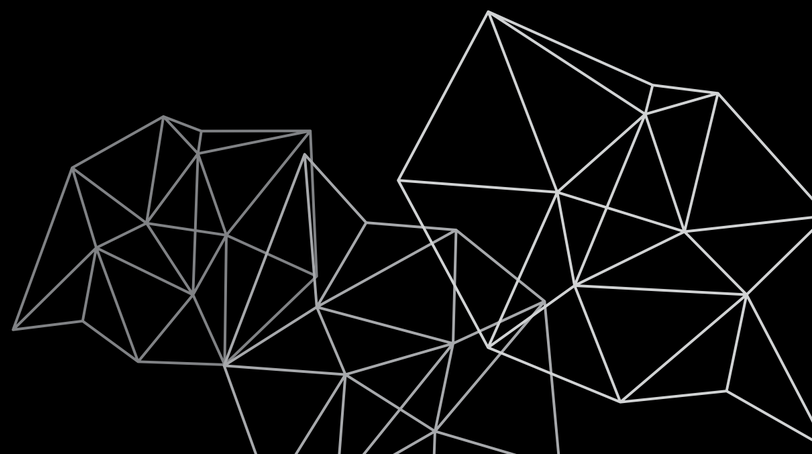
OBJECTIVE

- To use GRU (Gated Recurrent Unit) for time series forecasting
- To integrate data from multiple companies
- To make the model flexible for different forecast horizons (1d, 7d, 30d)
- To compare performance on different time intervals (5-min vs 1-day)

GRU

GRU gives us a lightweight yet powerful way to model sequential patterns (like stock or sensor data) because its gating mechanism retains important past information while being faster and simpler to train than LSTM. For the hackathon constraints — limited compute and dataset size — GRU is an efficient, high-impact choice





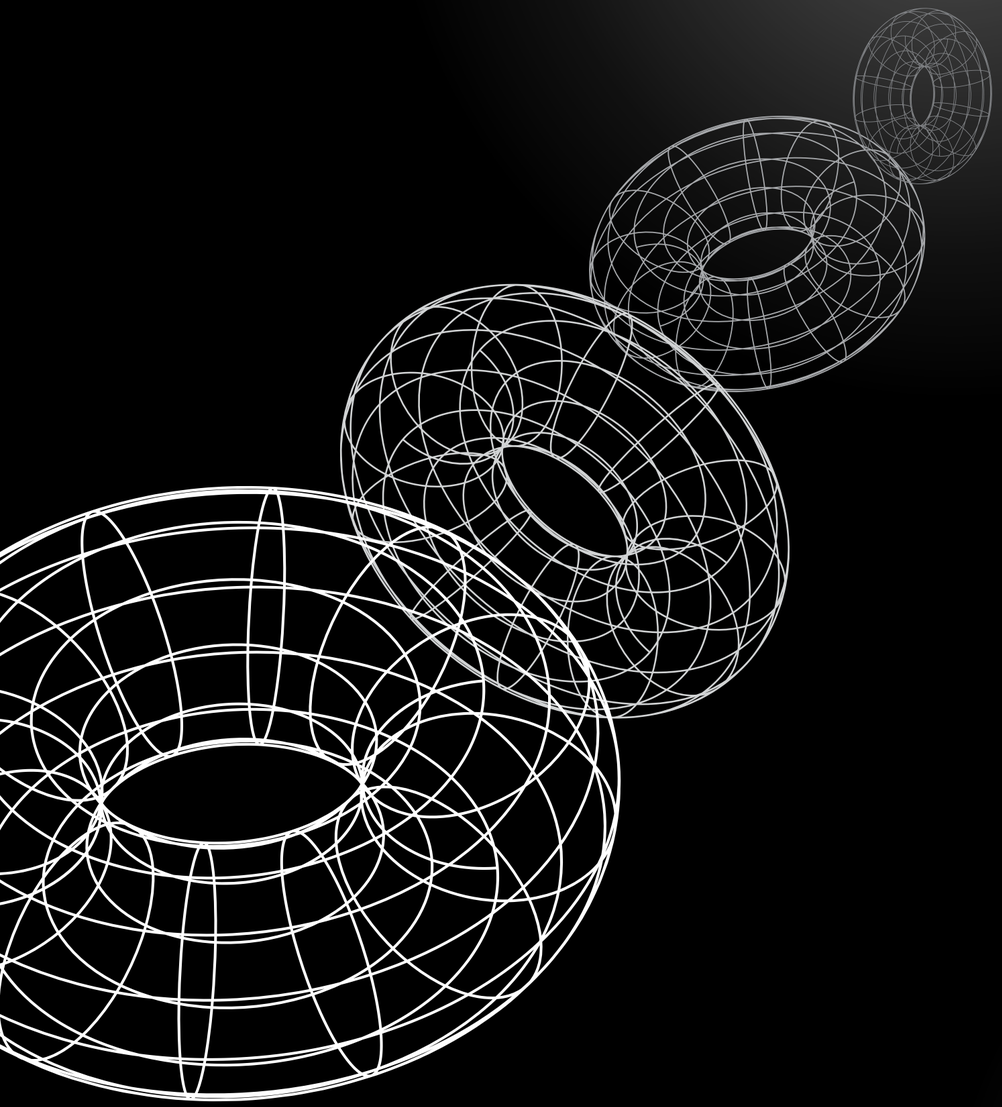
USE OF ML MODEL FOR PREDICTING FUTURE STOCK VALUES

Forecasting Trends: Helps estimate future prices (close, open, high, low) based on historical patterns.

Investment Decisions: Assists traders and investors in making buy/sell/hold decisions with data-driven insights.

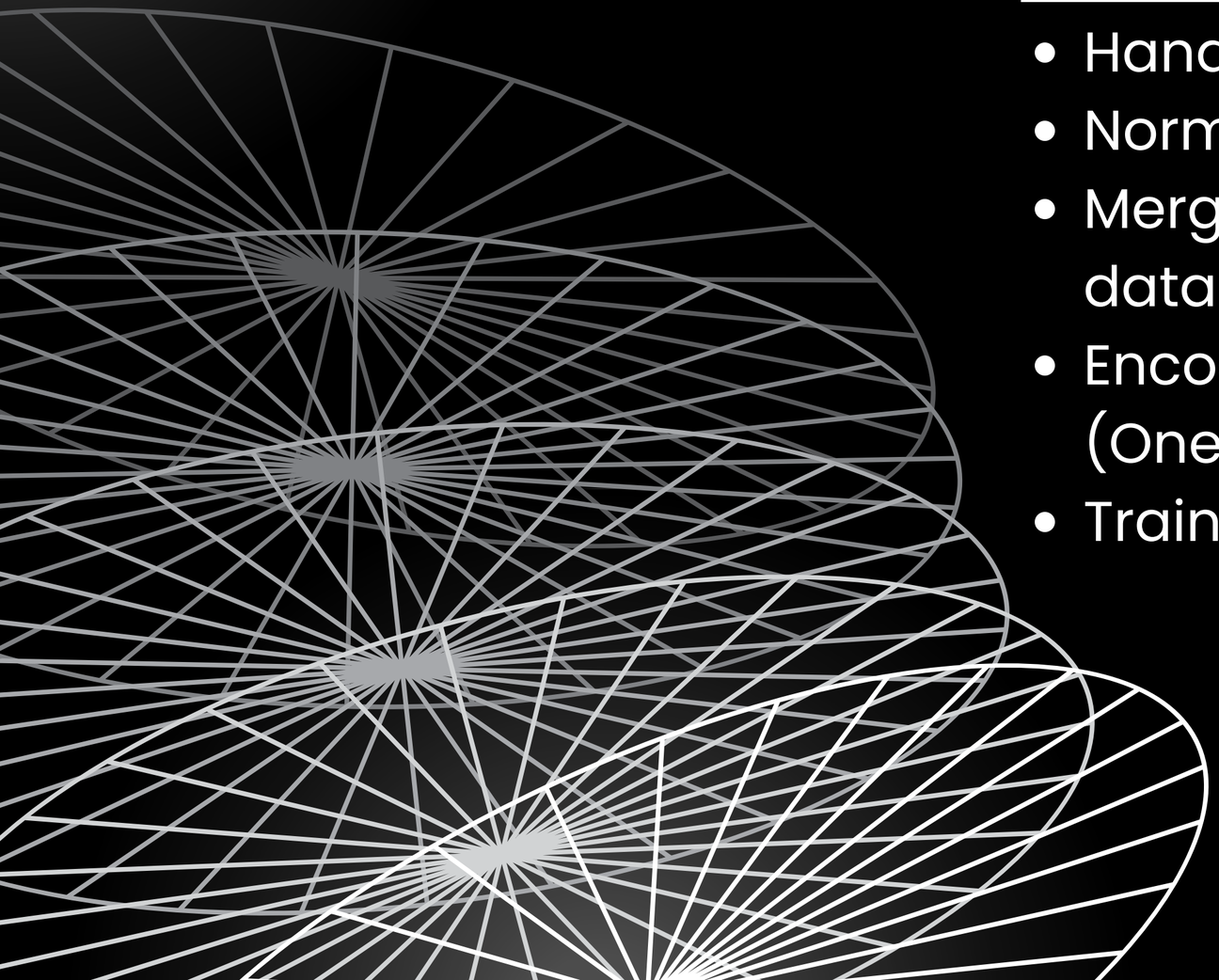
Risk Management: Identifies potential market volatility or downturns in advance.

Automated Trading: Enables algorithmic systems to execute trades automatically when certain price patterns or thresholds occur.



DATASET AND SOURCES

- **Data Sources:**
  - yfinance, EODHD
- **Data Description**:
  - No. of companies: 3
  - Total records: ~1215 per company
  - Features: Open, High, Low
  - Target : Close price
- **Frequency:** 5-min or 1-day intervals



DATA PREPROCESSING

- Handling missing data
- Normalization/scaling
- Merging multiple companies' data
- Encoding company identifiers (OneHotEncoder / get_dummies)
- Train-test split

MODEL ARCHITECTURE

A simple Sequential GRU model is built for each company:

GRU layer with **100** units (captures temporal dependencies)

Dropout (0.2) to prevent overfitting

Dense layer (1 unit) for predicting the next closing price

Optimizer: Adam (learning rate = 0.001)
Loss function: Mean Squared Error (MSE)

PREDICTION & EVALUATION

THE TRAINED GRU MODEL PREDICTS FUTURE CLOSING PRICES ON UNSEEN TEST DATA.

PREDICTIONS (SCALED 0–1) ARE INVERSE-TRANSFORMED USING MINMAXSCALER TO RETURN TO THE ORIGINAL PRICE RANGE.

MODEL PERFORMANCE IS VISUALLY COMPARED WITH REAL PRICES FOR EACH COMPANY.

PLOT COMPARISON

BLACK LINE: ACTUAL CLOSING PRICE

GREEN LINE: PREDICTED CLOSING PRICE

➡ CLOSER OVERLAP SHOWS HIGHER ACCURACY AND BETTER LEARNING OF STOCK TRENDS.
➡ VISUAL RESULTS HIGHLIGHT PATTERNS, LAGS, AND MODEL RELIABILITY ACROSS COMPANIES.

TRAINING DETAILS

Dataset split: **80%** for training, **20%** for testing to evaluate model generalization.

Optimizer: Adam – adaptive learning for faster and stable convergence.

Loss Function: Mean Squared Error (MSE) – measures average squared prediction error.

EarlyStopping: Monitors validation loss, stops training if no improvement for 10 epochs → prevents overfitting.

FUTURE PRICE PREDICTION RESULTS

THE TRAINED GRU MODELS ARE USED TO PREDICT FUTURE CLOSING PRICES FOR MULTIPLE COMPANIES.

Example predictions on 17th October 2025:

TATA: ₹173.19

Reliance: ₹154.92

MRF: ₹155,912.70

The predictions are generated using company-specific GRU models trained on historical data.

Indicates the model's capability to forecast future stock trends accurately.

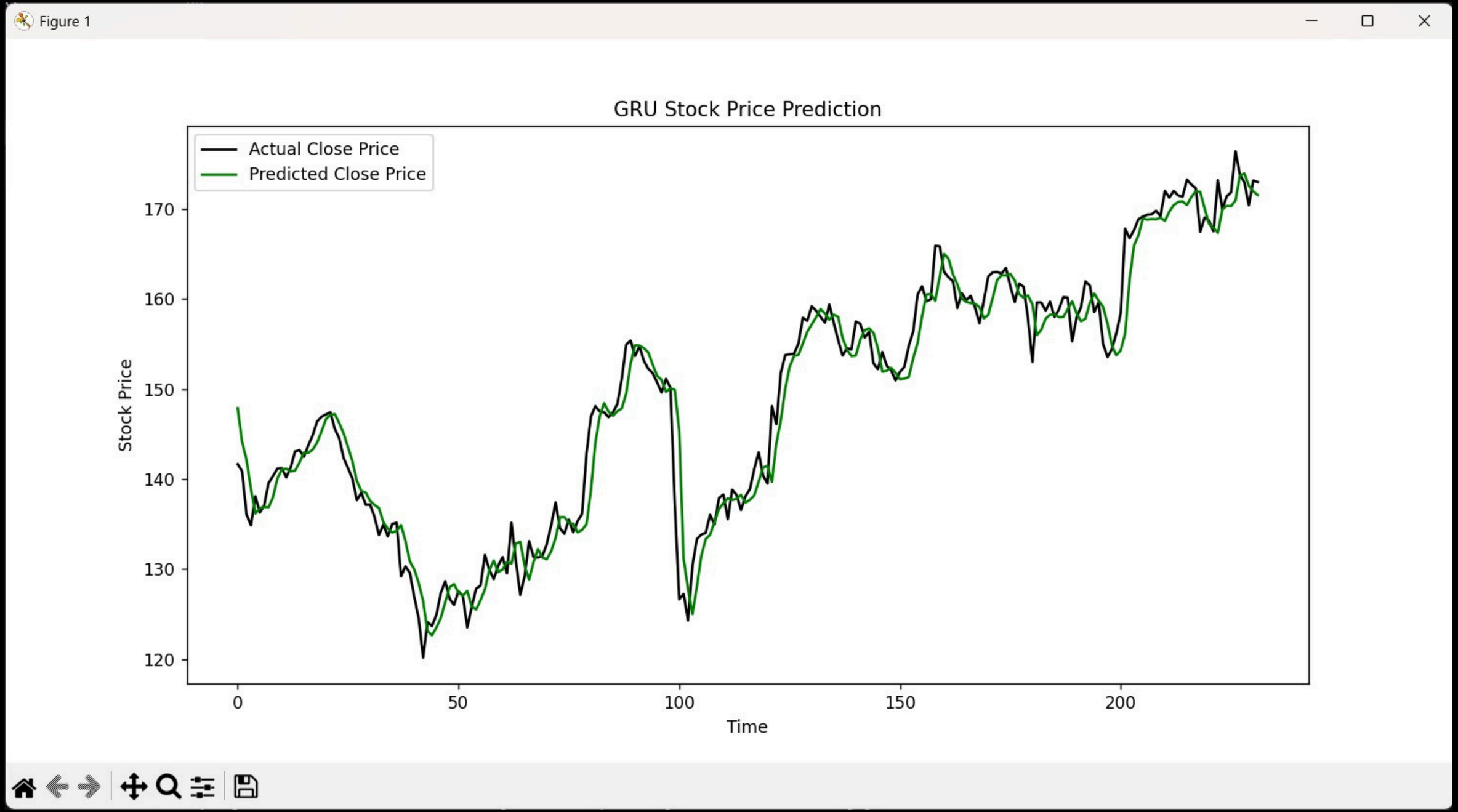


Figure 1
GRU Stock Price Prediction
Actual Close Price
Predicted Close Price
Stock Price
Time
120
130
140
150
160
170
0
50
100
150
200

CONCLUSION

Result: GRU effectively predicts stock closing prices, closely following actual trends Dropout layers improve generalization, handling sequential stock data efficiently.

Limitations: sudden market shocks not predictable; current model uses only OHLC features.

Future Work: hybrid GRU-ARIMA models, multi-stock prediction, automated retraining pipeline.