HYBRID GRU-LSTM WITH INTEGRATED FUNDAMENTAL & TECHNICAL ANALYSIS FOR

STOCK PRICE PREDICTION

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Outline

Why stock price prediction?

- Stock price prediction is a crucial task for investors and financial institutions, enabling informed decisions and risk management (Shah, 2023).

- A range of studies have explored the predictive ability of fundamental and technical analysis in stock price movement.

- Agustin (2019) found that while each approach can independently predict stock prices, their integration can enhance predictive power.

- The unpredictable nature of stock prices remains challenging, prompting the need for more accurate prediction algorithms (Gnanavel, 2023).

Problem Statement

Limitation of Fundamental & Technical Analysis

Fail to capture the multifaceted factors influencing stock prices.

Limitation of LSTM standalone model

Underperform when compared to other hybrid models.

Aims & Objectives

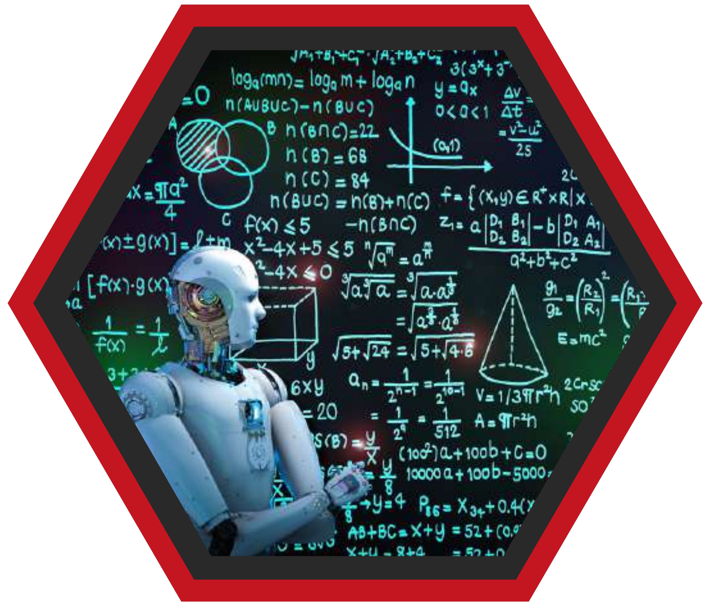
Objectives

- To develop a hybrid model that integrates GRU, LSTM, and fundamental analysis, leveraging their complementary strengths.
- To evaluate the performance of the hybrid model using performance metrics including RMSE, MAE and MSE.
- Investigate the impact of varying the number of layers in GRU and LSTM architectures on the performance and accuracy of predicting stock price trends.
- To evaluate the performance of the enhanced predictive model with evaluation metrics such as MSE, RMSE, MAE, and MAPE.

Literature Review

Stock Price Prediction Models

Traditional Statistical Model



Machine Learning Model

Deep Learning Model

Traditional Statistical Model

- Autoregressive Integrated Moving Average (ARIMA)
- works based on the outcomes and the related dependencies where the past values are inputted and the future values are produced
- useful when dealing with linear and stationary data patterns
-

AR

AutoRegressive (AR) for looking at past observations

I

Differencing (I or Integrated) for handling changes in data patterns

MA

Moving Averages (MA) for considering error terms

Machine Learning (ML) Models

Support Vector Regression (SVR)

✓ Captures non-linear dependencies

✓ Handles noisy market data

✗ Limited scalability

✗ No sequential processing

Random Forests (RF)

✓ Handles non-linear features

✓ Good feature combination

✗ No temporal dependencies

Extreme Gradient Boosting (XGBoost)

✓ Most efficient (MSE: 0.004)

✓ Strong feature handling

✗ No temporal dependencies

Deep Learning (DL) Models

RNN Recurrent Neural Networks

Capabilities

→ Process variable-length sequences

→ Learn temporal patterns

→ Capture market dynamics

Advantages

✓ Superior sequence learning

✓ Time series specialization

✓ Convolutional perception

LSTM Long Short-Term Memory

Specialized for capturing long-term market patterns and dependencies

GRU Gated Recurrent Unit

Streamlined architecture offering computational efficiency

Long Short-Term Memory (LSTM)

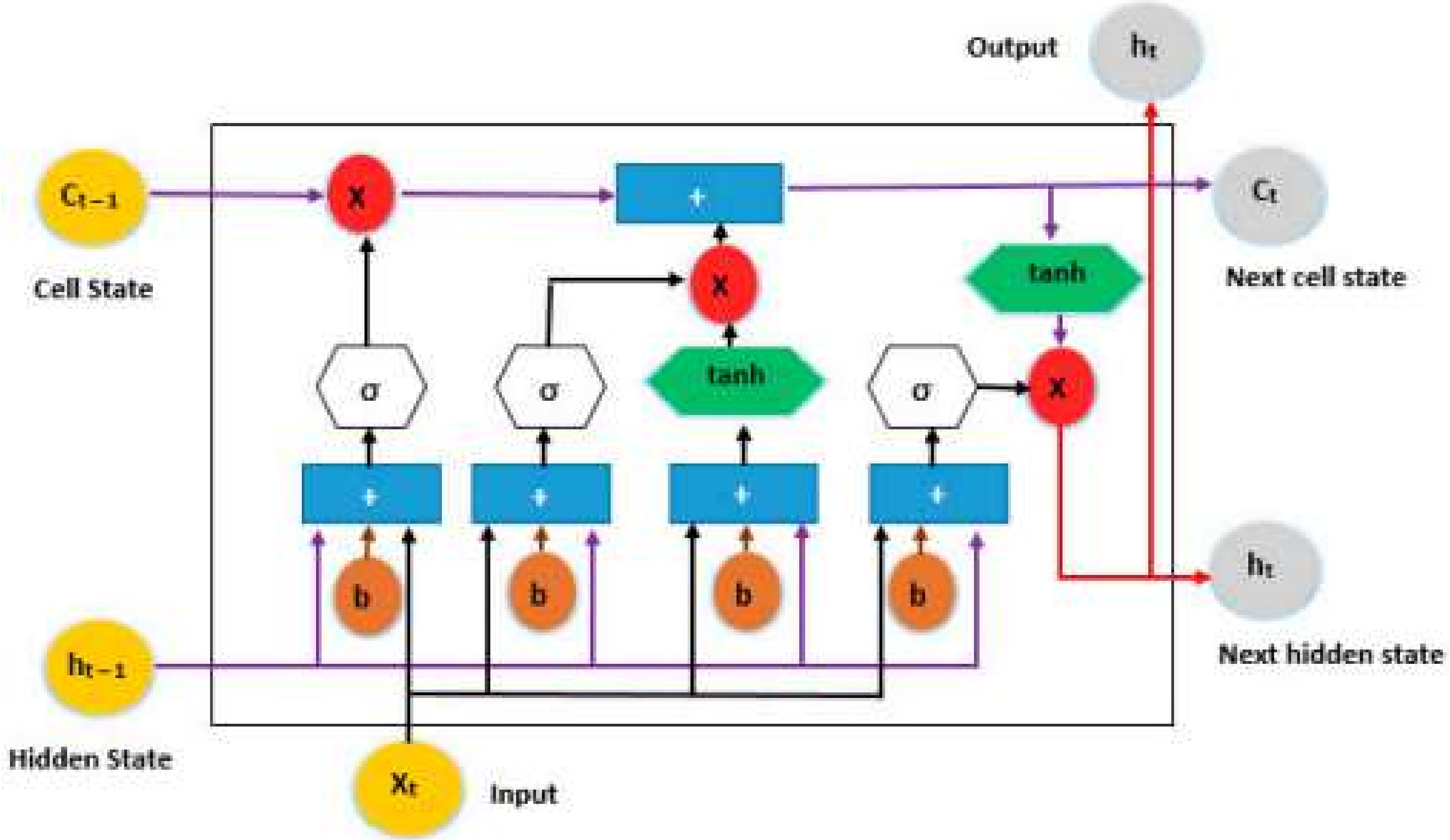


Figure 2.1: Structure of a LSTM algorithm (Hamayel & Owda, 2021).

proficiency in handling time-series data
maintaining a memory of previous states, LSTM networks can capture trends and patterns over long periods

ability to deal with noise in data
filter out the noise and focus on the underlying patterns of the data as shown Ma (2020)

computationally intensive
complexity of the model requires substantial computational resources

prone to overfitting
Techniques like regularization, dropout and cross-validation can be used to mitigate this issue

Variant of LSTM

A type of RNN that has gained popularity in time-series forecasting tasks

Address the vanishing gradient problem

Use gating mechanisms to control the flow of information

GRU network has one less gate than the LSTM

- only two gates: reset gate and update gate
- The smaller the value of the reset gate, the more memory is ignored
- The greater the value of the update gate, the more information it will generate

Computationally more efficient than LSTM

- fewer parameters
- reduces the computational burden
- attractive option for real-time stock prediction applications

(Zhang and Aggarwal, 2021).

Gated Recurrent Unit (GRU)

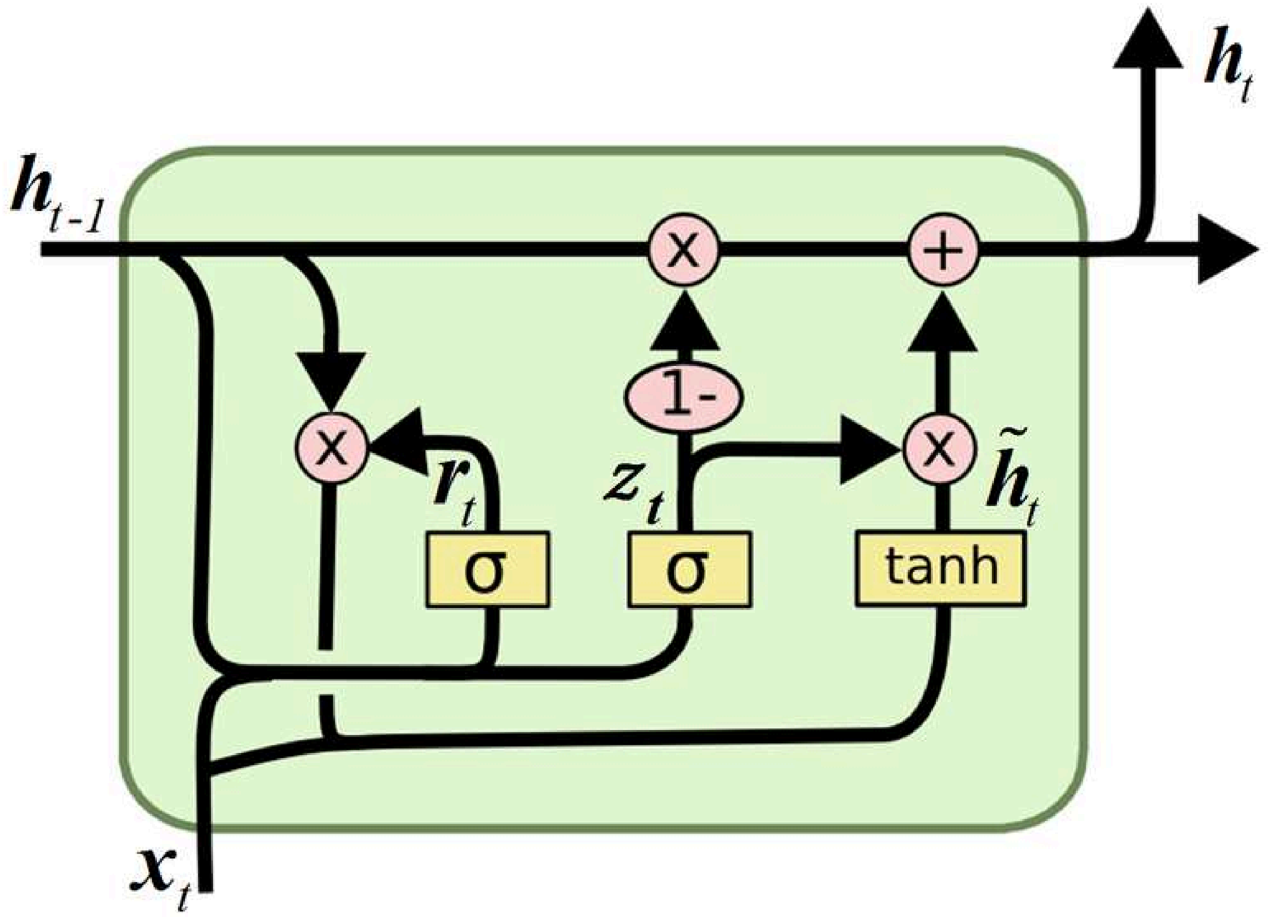
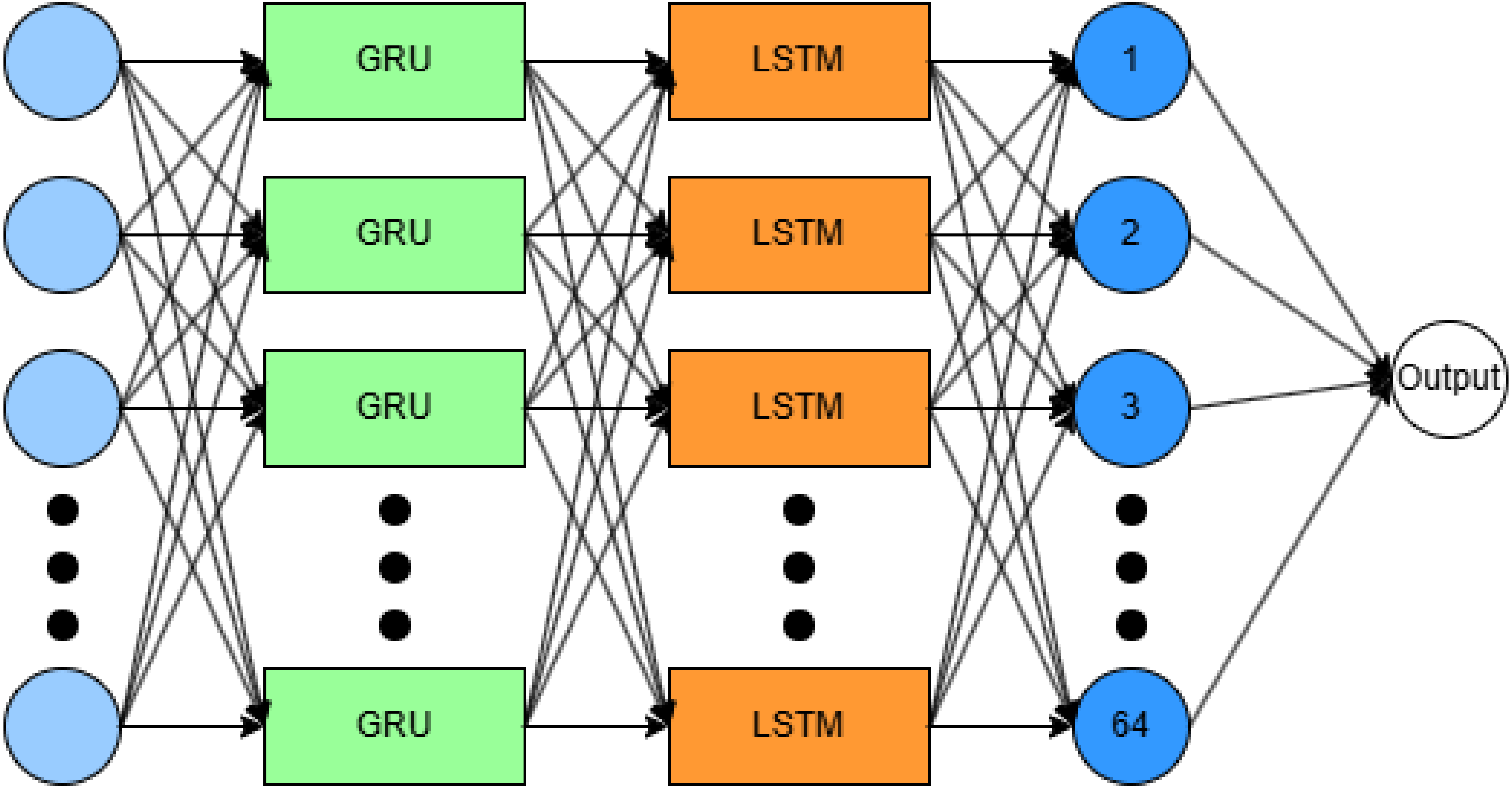


Figure 2.1: Structure of a GRU algorithm (Jin et al., 2020).

Hybrid GRU-LSTM Architecture



Hybrid GRU-LSTM Architecture

Applications across domains

- Financial market： Stock price prediction， Cryptocurrency trends
- Other fields: Traffic prediction, Anomaly detection, COVID-19 trends

Key advantages

- Superior performance vs. single models
- Handles multiple data sources
- Better accuracy metrics (MSE, RMSE, MAPE)

Recent advancements

- Swarm intelligence enhancement for intrusion detection (Al-kathari et al., 2023)
- Attention mechanisms for cryptocurrency prediction (Chen et al., 2023)

Stock prediction methods can be classified into 2 main categories (Huang et al., 2021).

Fundamental Analysis

- analysis of a company's intrinsic value via its published financial reports (Qin and Boicu, 2023)
- financial position, employees performance, yearly report, balance sheets, income reports
- financial ratios like D/E, P/S, P/B and EPS ratio.

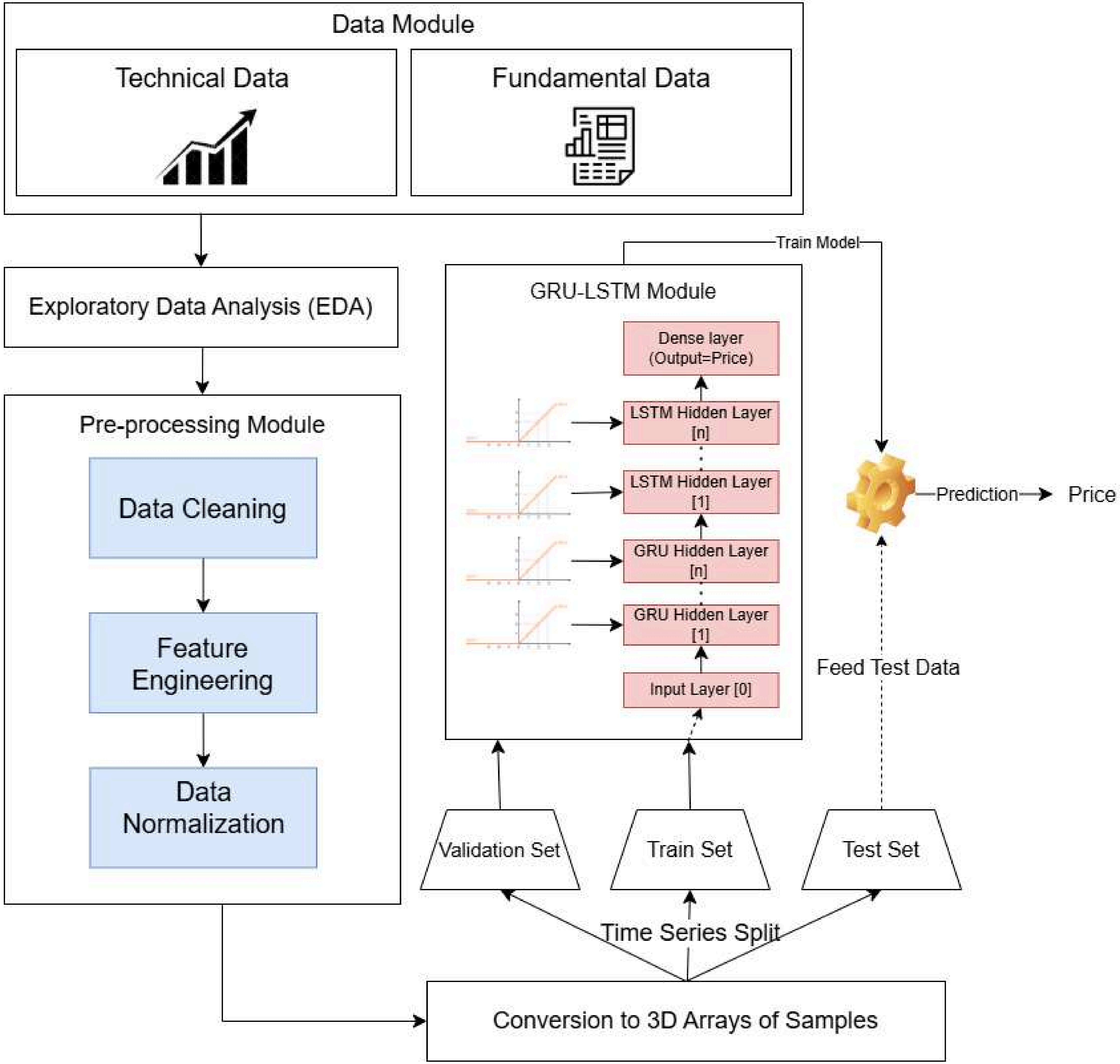
Technical Analysis

- analysis of market activity such as historical price data, sentiments, flow-of-funds and cycle.
- technical analysts; aim to predict stock movement in the short run.
- risky over long time horizons since it does not take the fundamentals of company's health into account (Kaushik, 2024).

Research Methodology

Research Design

- quantitative and experimental methodology
- utilizes machine learning techniques
- mainly consists of three modules
- Data Module, Pre-Processing Module and GRU-LSTM Module.



Step 1 : Data Module

- data collected using Yahoo Finance API
- 2 stocks： Dalian Friendship(Group)Co.Ltd.(000679.SZ)
- Dalian Thermal Power Co.,Ltd.(600719.SS)
- Open, High, Low, Close, Volume, Dividends & Stock Splits
- 2430 rows and 7 columns

Step 2: Preprocessing Module

- Exploratory Data Analysis
- Data Celaning
- Feature Engineering
- Data Normalization
- Data Transformation
- Data Splitting
- Data Augmentation
- Data Validation

Exploratory Data Analysis (EDA)

- Understand data structure and distributions.
- Identify trends, anomalies, and outliers.
- Columns analyzed include Open, High, Low, Close, Volume, Dividends, and Stock Splits
- Line plots for stock price trends.
- Histograms for price distributions

Data Cleaning

- Ensure data quality and consistency
- Remove irrelevant or redundant information.
- Checked with data.isnull().sum()—no missing values found.
- Confirmed no duplicates exist.
- Columns like Dividends and Stock Splits excluded as they don't contribute to predictions.
- Removed as it lacks numerical significance.

Feature Engineering

Purpose of Feature Engineering

- Enhance the dataset to improve the model's ability to capture patterns and trends.
- Generate additional meaningful features that aid predictive accuracy.

Features Added

- Moving Averages
- Stochastic Indicators
- Moving Average Convergence Divergence (MACD)
- Relative Strength Index (RSI)

Data Normalization

Purpose:

- Bring all features to a comparable scale.
- Enhance model convergence and reduce training time.
- Avoids dominance of features with larger scales.

Method Used

- Min-Max Scaling:
- Transforms data to a range of [0, 1].
- Applied to features such as Open, High, Low, Close, and Volume.

Data Transformation

Purpose:

- Enable compatibility with the GRU-LSTM model, which requires data in sequential (3D) format.
- Preserve temporal dependencies critical for time-series forecasting.

Propotions:

- Transformed dimensions: (samples, time steps, features).
- Example: If 100 samples, 10 time steps, and 5 features → final shape is (100, 10, 5).

Data Splitting

Purpose:

- Bring all features to a comparable scale.
- Ensure that the model is evaluated on unseen data to simulate real-world performance

Propotions:

- Training Set: 64% of the dataset – used to learn model weights.
- Validation Set: 16% of the dataset – used for hyperparameter tuning and performance monitoring.
- Test Set: 20% of the dataset – reserved for evaluating model accuracy on unseen data.

Step 3 : GRU-LSTM Module

- combines both GRU and LSTM layers in a way to take advantage of the 'best of both worlds
- GRU provides computational efficiency
- LSTM provides robust handling of long-term dependencies.
- Input layer, GRU, LSTM, and dense output layer
- Rectified Linear Unit (ReLU) activation function
- dense output layer (regression layer)
- MSE loss function

Step 4 : Training and Validation

Importance of Training and Validation

- Ensures the GRU-LSTM hybrid model effectively learns patterns in stock price data.
- Validates the model’s ability to generalize to unseen data

Propotions:

- Training Set: 64% of the dataset – used to learn model weights.
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Step 4 : Training and Validation

Training Configuration

- **Optimizer:** Adam optimizer dynamically adjusts the learning rate for efficient convergence.
- **Batch Size:** 64 samples per batch for computational efficiency.
- **Epochs:** Model trained over 20 epochs to balance learning and avoid overfitting.
- **Loss Function:** Mean Squared Error (MSE) minimizes the difference between predicted and actual stock prices.

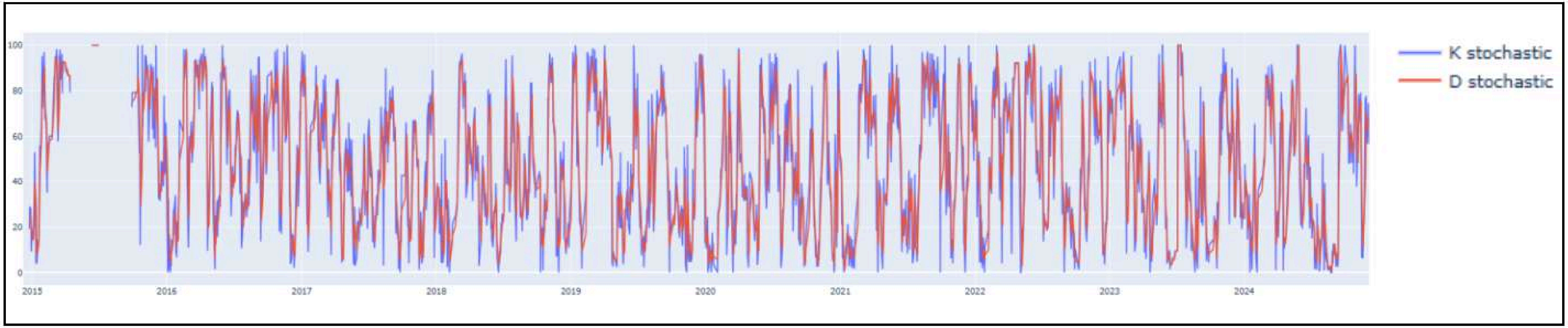
Step 5 : Model Evaluation

- Validate the model's ability to predict stock prices accurately and robustly.
- Use the following error metrics to provide a comprehensive understanding of model performance:

1. Mean Absolute Error (MAE)
2. Mean Absolute Percentage Error (MAPE)
3. Mean Squared Error (MSE)
4. Root Mean Squared Error (RMSE)

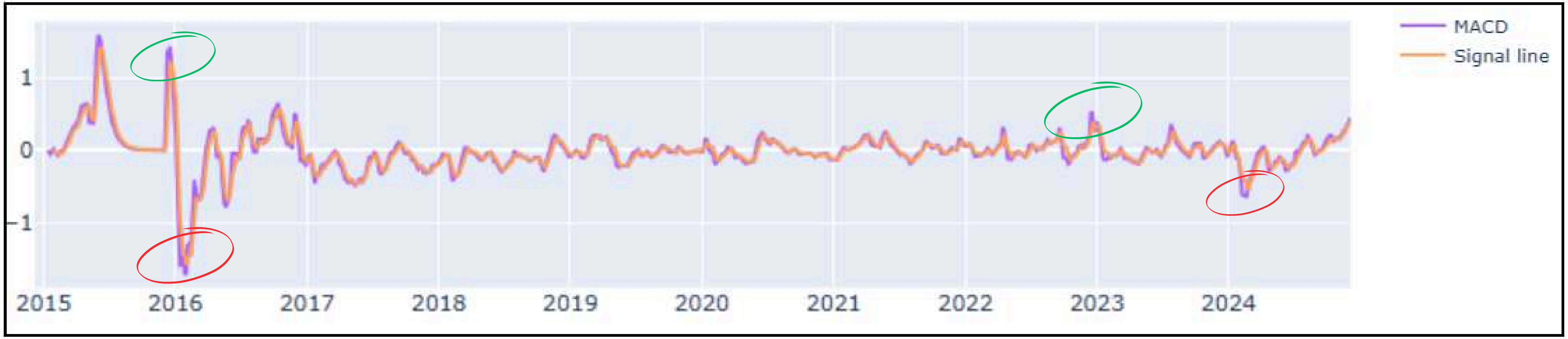
Research Findings

Feature Analysis - Stochastic Indicators



- give information on the direction of the market
- over-bought - values close to 100
- over-sold - values close to zero
- intersections of the K and D lines are used as buy/sell signals
- K line is seen to crossover the D line upwards, this depicts a bullish situation
- Otherwise, it depicts a bearish situation.

Feature Analysis - MACD & Signal line

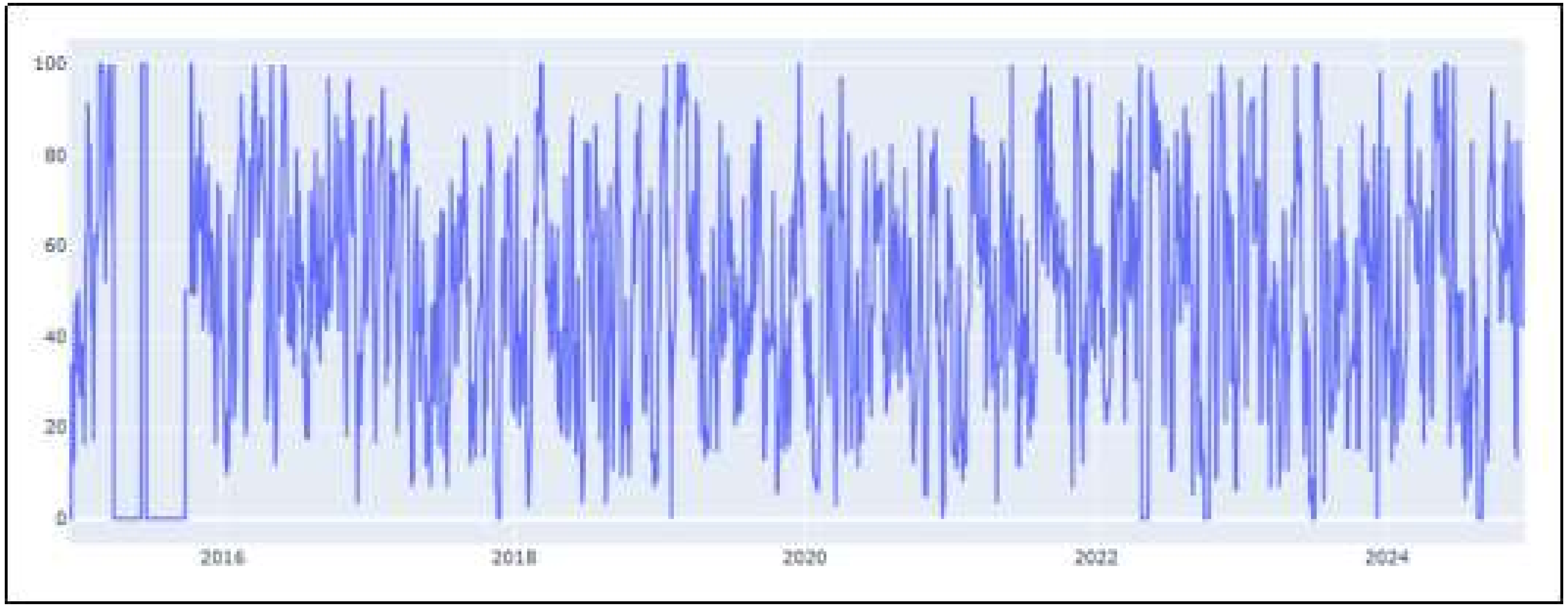


- Identify momentum shifts in stock prices.
- Bullish Signal: MACD crosses above the signal line.
- Bearish Signal: MACD crosses below the signal line.
- Highlights key momentum shifts and trend reversals.

Feature Analysis - EMA

- 50-day MA/EMA: Represents short-term trends in stock prices.
- 200-day MA/EMA: Reflects long-term price trends.
- Golden Cross: 50-day MA/EMA crosses above the 200-day MA/EMA
- Death Cross: 50-day MA/EMA crosses below the 200-day MA/EMA.

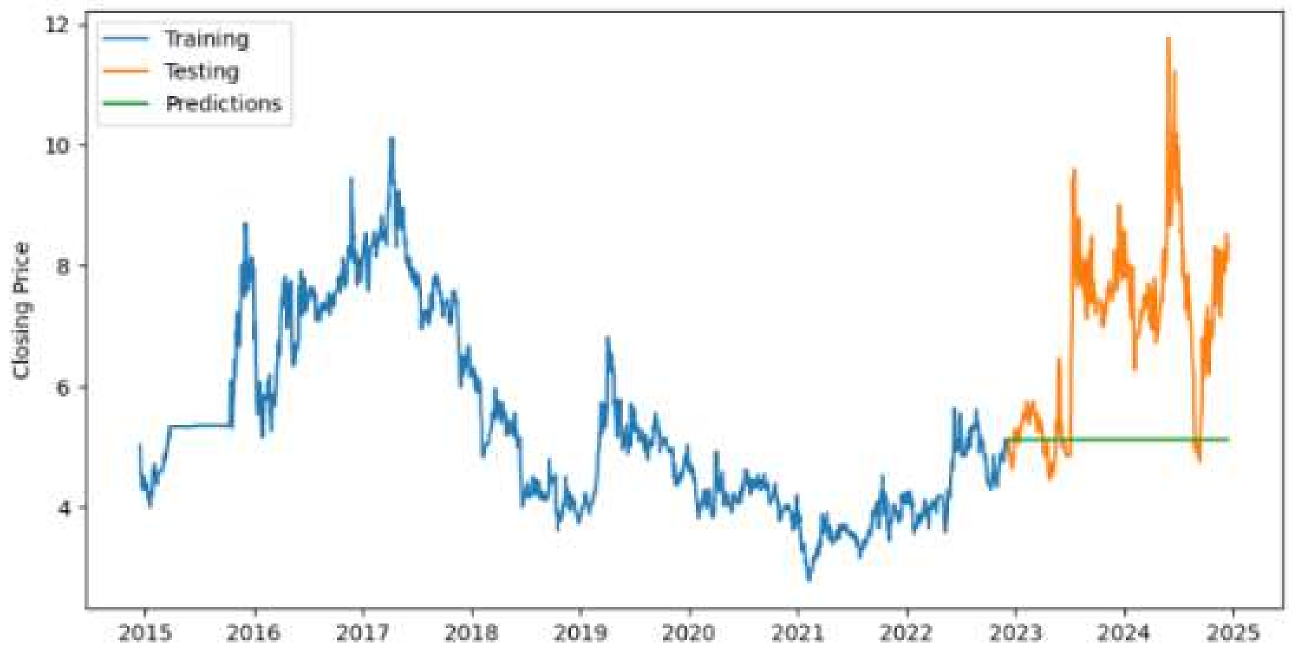
Feature Analysis –RSI

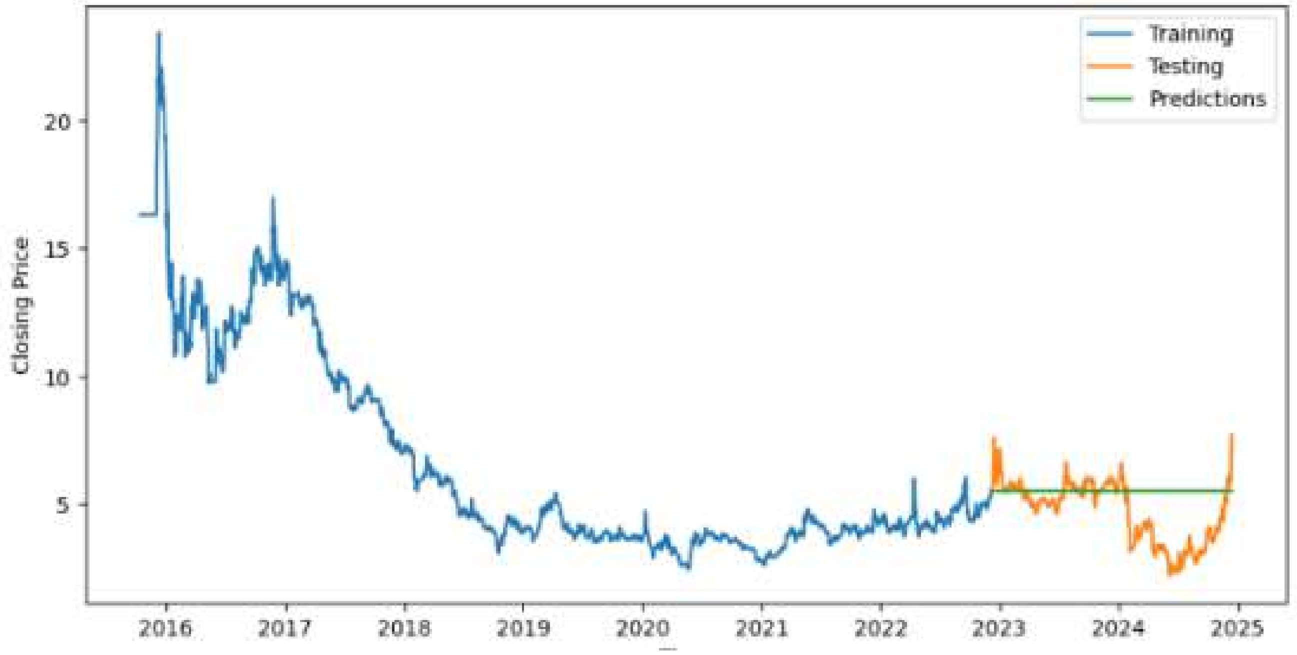


- measures the speed and change of price movements.
- Values range from 0 to 100, indicating overbought or oversold conditions.
- RSI > 70: Overbought condition.
- Indicates a potential price decline.
- RSI < 30: Oversold condition.
- Indicates a potential price increase.

Performance of Models

Performance Metrics of the ARIMA Model





Observations:

- ARIMA struggles to capture sudden market spikes or drops.
- Noticeable lag in adjusting to new trends.
- Predictions are over-smoothed, lacking responsiveness to rapid market changes.

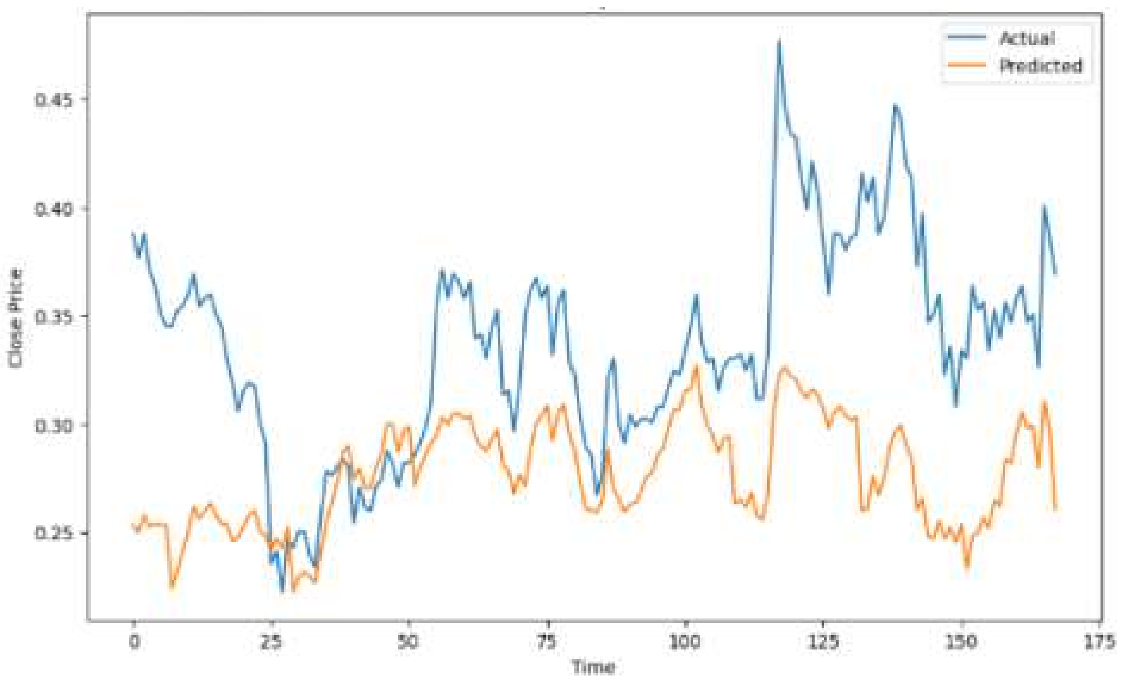
Key Limitations:

- ARIMA assumes market data is stationary, which is rarely the case in real-world volatile stock markets.
- Unable to adjust quickly to dynamic and non-linear price movements.

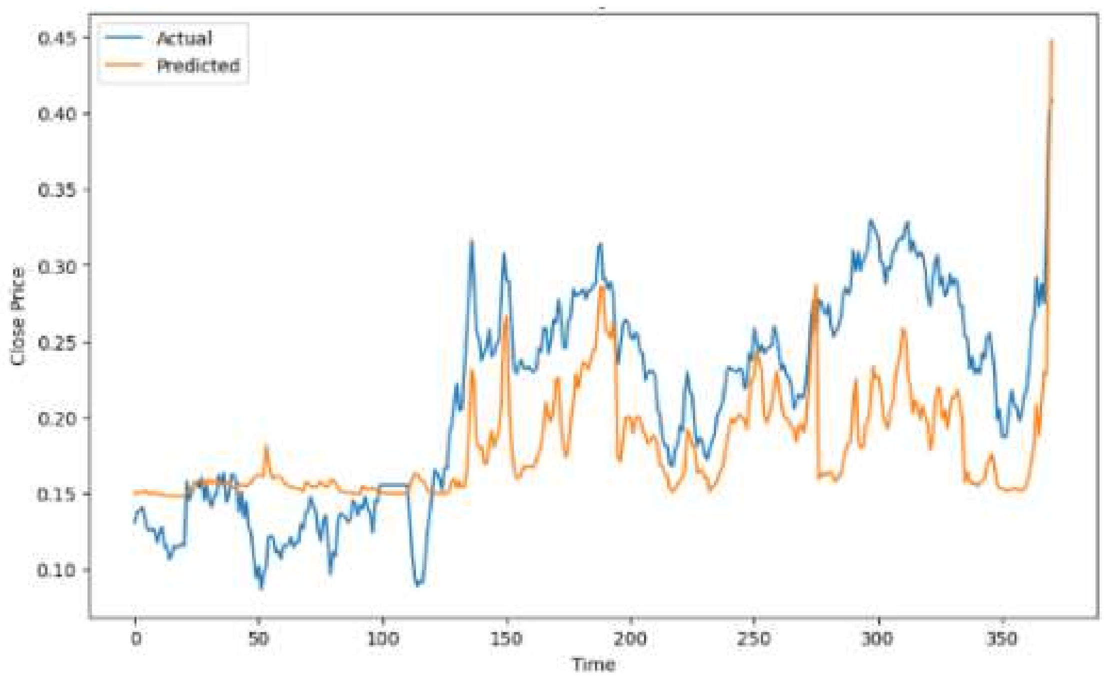
Performance Metrics of the ARIMA Model

Stock	Metrics		
	MSE	RMSE	MAE
000679	2.055	1.434	1.059
600719	5.408	2.326	1.912

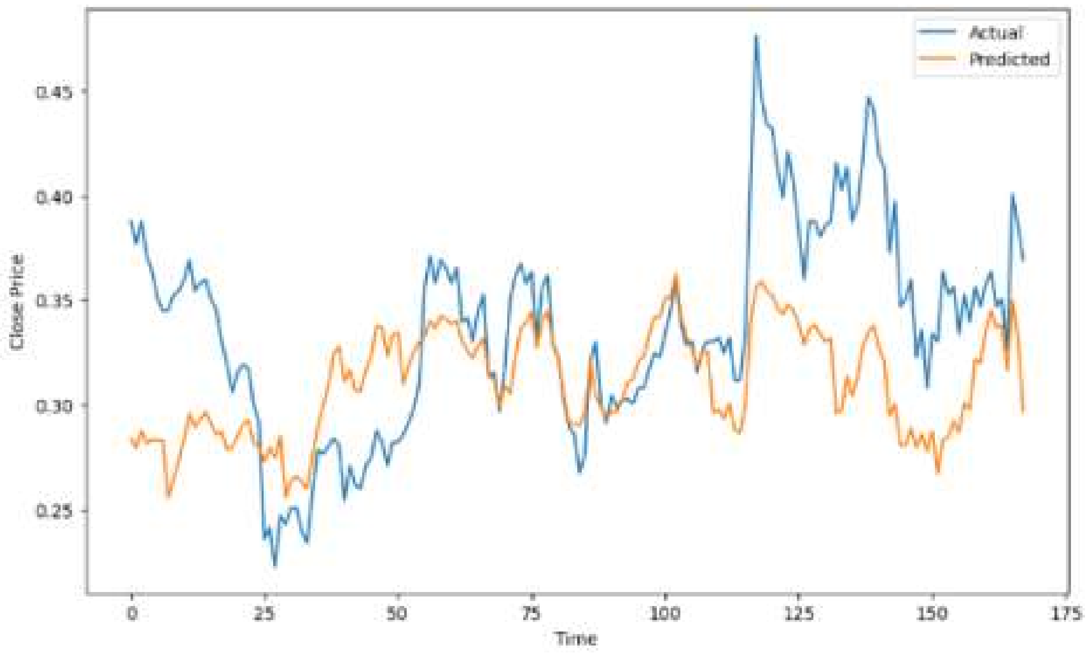
Performance Metrics of the Standalone Models



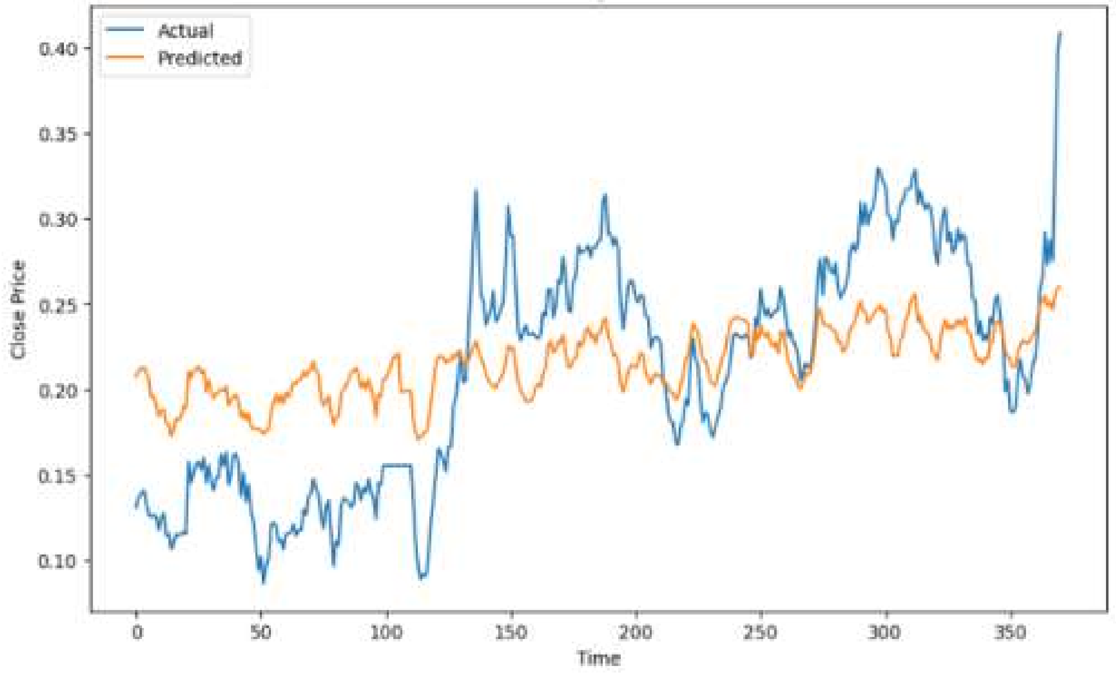
LSTM - 000679



LSTM - 600719



GRU- 000679



GRU- 600719

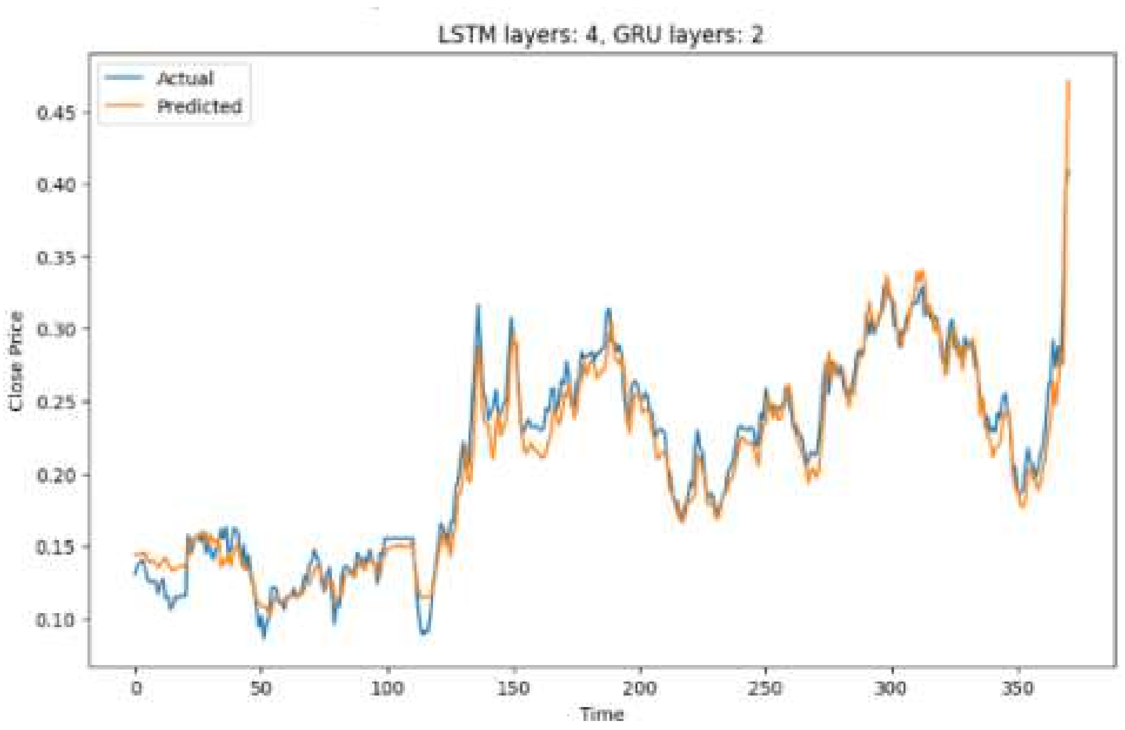
Performance Comparison:

- GRU demonstrates superior performance for both stocks
- Lower RMSE
- Consistent predictions during volatile market conditions.
- LSTM shows advantages in percentage-based deviations
- Lower MAPE: Handles certain scenarios involving relative errors more effectively.

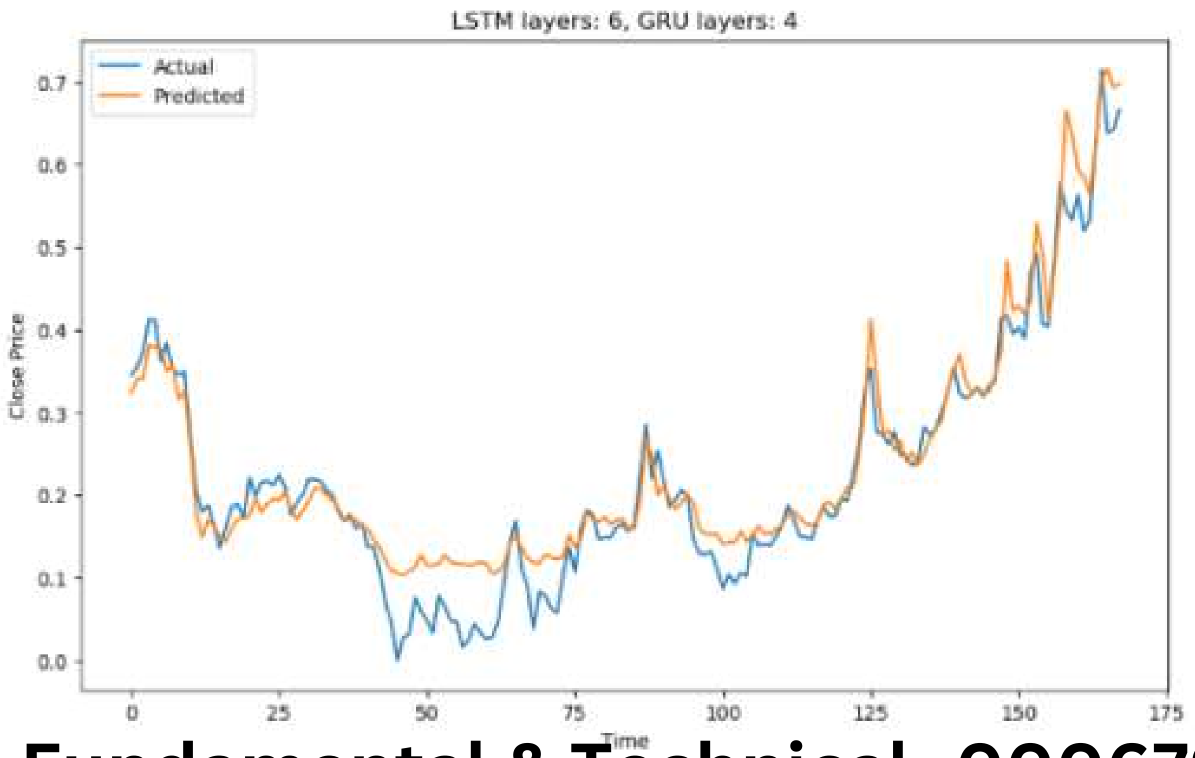
Performance Results of GRU and LSTM Standalone Models

Evaluation		Metrics			
Stock	**Model**	**MSE**	**RMSE**	**MAE**	**MAPE**
600719	GRU	0.0029	**0.0542**	0.0463	0.2835
	LSTM	0.0032	0.0566	0.0474	**0.2221**
000679	GRU	0.0025	**0.0505**	0.0406	0.1164
	LSTM	0.0030	0.0545	0.0384	**0.0842**

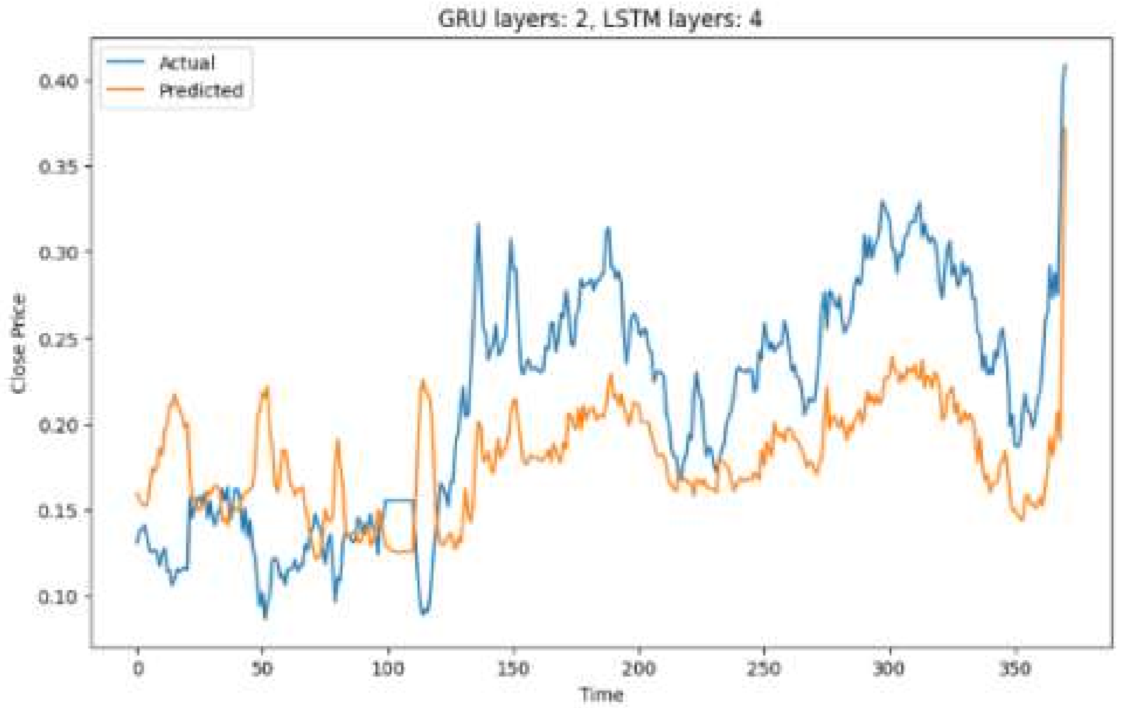
Performance of Hybrid GRU-LSTM Model



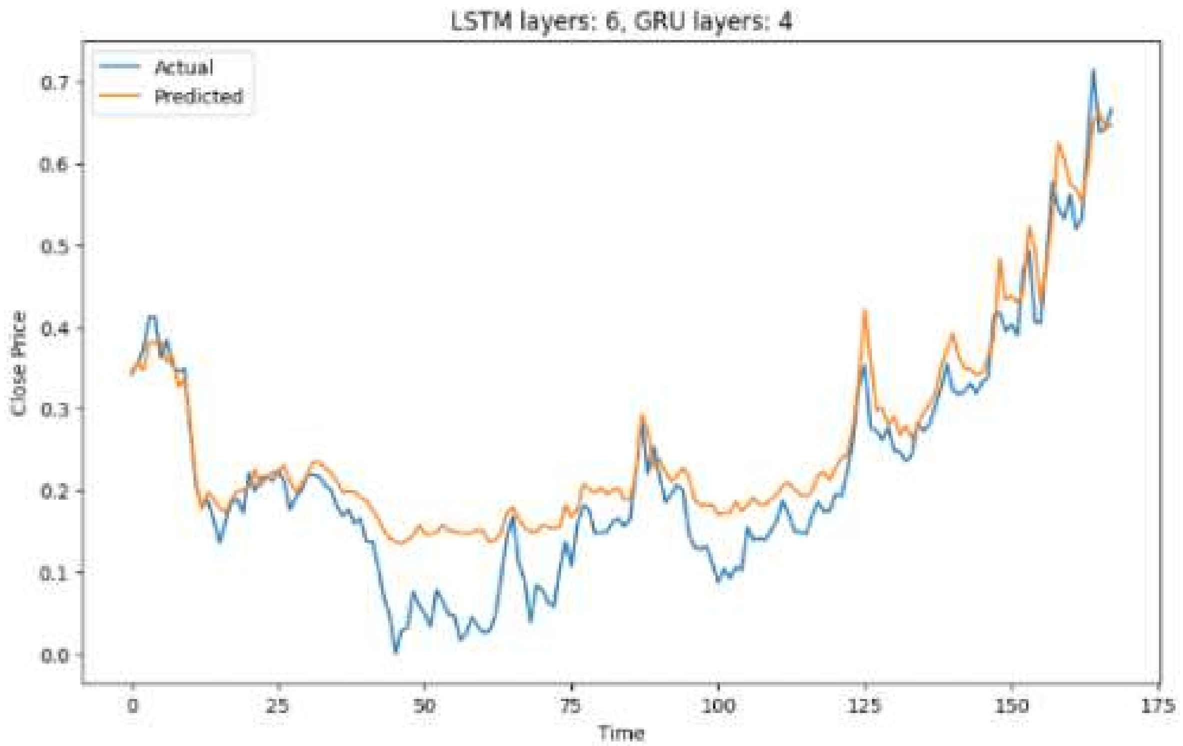
Fundamental & Technical - 600719



Fundamental & Technical -000679



Technical Only - 600719



Technical Only -000679

Performance Results of the Hybrid GRU-LSTM Models

Evaluation		Metrics			
Stock	Data	MSE	RMSE	MAE	MAPE
600719	Fundamental & Technical	0.0002	**0.0141**	0.0111	0.0569
	Technical Only	0.0036	0.0601	0.0540	0.2659
000679	Fundamental & Technical	0.0013	**0.0360**	0.0269	0.0587
	Technical Only	0.0022	0.0474	0.0348	0.0610

Effect of GRU and LSTM Layer Configurations

Trade-off Between Complexity and Accuracy:

- Excessive layers → Overfitting.
- Few layers → Less precise predictions.
- Moderate layers → Best performance.
- Layer configuration depends on the stock's characteristics.

Different Optimal Configurations for Each Stock:

- Stock 000679: 4 GRU, 6 LSTM.
- Stock 600719: 2 GRU, 4 LSTM.

Conclusion

Conclusion

- Design a hybrid model for stock price prediction using LSTM, GRU and fundamental analysis.
- Outperformed conventional methods across multiple metrics
- Successfully tested on two stock datasets: 600719 & 000679
- Combined GRU's computational efficiency with LSTM's long-term dependency capture
- Enhanced robustness through fundamental indicator integration

Future Works

Sentiment Analysis Integration

- Incorporate market sentiment from news articles, earnings reports, and social media

Enhanced Model Testing

- Test generalizability with larger, more diverse datasets

Fundamental Data Expansion

- Include EPS, P/E ratio, D/E ratio, and P/B ratio using US market data

Real-time Framework

- Develop real-time prediction system for practical market applications

Thank You

For Your Attention