End-to-End Deep Learning Model for Stock Price Prediction

1: Introduction

This project focuses on developing an end-to-end deep learning framework for stock price prediction using time-series analysis. The primary objective is to accurately forecast stock closing prices by leveraging advanced neural network architectures capable of modeling sequential financial data. Traditional statistical models often fail to capture complex nonlinear relationships present in stock markets. Therefore, this study compares three deep learning models: Long Short-Term Memory (LSTM), CNN-LSTM, and a proposed Hybrid CNN + Bidirectional LSTM architecture. By analyzing their predictive performance using regression metrics such as RMSE and MAE, the research aims to determine which architecture provides superior accuracy and stability for real-world financial forecasting applications.

2: Literature Review

Time-series prediction has significantly benefited from deep learning techniques, particularly LSTM networks, which are designed to capture long-term dependencies in sequential data. LSTM models are widely applied in stock market forecasting due to their memory cell structure, which retains historical information over time. Convolutional Neural Networks (CNNs), although originally developed for image processing, have shown effectiveness in extracting local patterns from time-series data when applied using one-dimensional convolutions. Recent research suggests that hybrid architectures combining CNN and LSTM outperform standalone models by leveraging both local feature extraction and sequential learning. However, many studies report relatively high prediction errors, indicating scope for architectural improvements.

3: Research Gap

Despite the success of LSTM-based forecasting models, standalone LSTM architectures may not efficiently capture short-term local variations alongside long-term dependencies. Similarly, CNN-LSTM models improve feature extraction but may not fully utilize bidirectional sequence learning, which can enhance temporal understanding. Existing implementations often result in higher RMSE and MAE values, indicating prediction instability. Therefore, there is a need for an improved hybrid architecture that integrates CNN for feature extraction and Bidirectional LSTM for enhanced temporal modeling. The proposed model aims to reduce prediction errors significantly and provide better generalization for real-world stock price forecasting.

4: Proposed Algorithm

The proposed approach begins with historical stock closing price data as input. The preprocessing stage includes handling missing values, applying Min-Max normalization for scaling between 0 and 1, and generating sequences of 100 time-steps for supervised learning. The model architecture consists of a Conv1D layer to extract local temporal patterns, followed by a MaxPooling layer for dimensionality reduction. A Bidirectional LSTM layer is then applied to capture forward and backward sequence dependencies. Dropout regularization is used to prevent overfitting, and a Dense layer generates the final predicted stock closing price. The model is trained using the Adam optimizer and Mean Squared Error loss function.

5: Architecture

The architecture of the proposed Hybrid CNN-BiLSTM model combines the strengths of convolutional and recurrent neural networks. The Conv1D layer identifies short-term fluctuations and local patterns in stock price movements. The MaxPooling layer reduces computational complexity while preserving essential features. The Bidirectional LSTM layer enhances temporal learning by processing sequence information in both forward and backward directions, improving contextual understanding. Dropout is incorporated to improve generalization by reducing overfitting during training. Finally, a Dense output layer performs regression to predict the closing stock price. This structured combination enables the model to capture both spatial and temporal dependencies effectively.

6: Dataset

- Dataset: Historical stock market data
- Features: Open, High, Low, Close, Volume
- Target Variable: Close Price
- Date Range: 2015-01-01 to latest
- Total Entries: 2348
- Sequence Length: 100 time-steps

7: Implementation Details

- Data sorted chronologically
- Scaled using Min-Max Scaler
- Sequence reshaping for LSTM input
- Epochs: 10
- Batch Size: 32
- Optimizer: Adam
- Loss Function: Mean Squared Error

8: Results

LSTM Model

RMSE: **17179.91**
MAE: **17173.81**

CNN-LSTM Model

RMSE: **16869.05**
MAE: **16862.83**

Proposed Hybrid Model (CNN + BiLSTM)

RMSE: **14762.31**
MAE: **14755.21**

Proposed Hybrid model achieved the lowest RMSE and MAE.

9: Comparative Analysis

Model	RMSE	MAE
LSTM	17179.91	17173.81
CNN-LSTM	16869.05	16862.83
Proposed Hybrid	**14762.31**	**14755.21**

Proposed hybrid model performs better than baseline models in both RMSE and MAE.

10: Evaluation Metrics

Mean Squared Error (MSE)

MSE=(1/n)∗Σ(ytrue−ypred)2MSE = (1/n) * Σ (y_true - y_pred)^2MSE=(1/n)∗Σ(ytrue−ypred)2

Mean Absolute Error (MAE)

MAE=(1/n)∗Σ|ytrue−ypred|MAE = (1/n) * Σ |y_true - y_pred|MAE=(1/n)∗Σ|ytrue−ypred|

Root Mean Squared Error (RMSE)

RMSE=sqrt((1/n)∗Σ(ytrue−ypred)2)RMSE = sqrt((1/n) * Σ (y_true - y_pred)^2)RMSE=sqrt((1/n)∗Σ(ytrue−ypred)2)

11: Output Visualizations

Chart 1: Actual vs Predicted Values

- Shows close alignment between predicted and actual prices
- Hybrid model tracks price trend more accurately
- Lower deviation compared to LSTM

Chart 2: Training vs Validation Loss

- Loss decreases steadily over epochs
- Minimal overfitting observed
- Validation loss closely follows training loss

12: Conclusion

- Hybrid CNN-BiLSTM model effectively predicts stock prices.
- Error metrics lower compared to single LSTM and CNN-LSTM.
- Model captures both local patterns and long-term dependencies.
- Recommended for time-series prediction tasks requiring higher accuracy.