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

🔷 **Research Paper Introduction**

Hello I'm Abhishek Pise , I'm from Tasgaon city , and I completed my Master's in 2025 in the subject of computer science.

I select the research paper on the deep learning developing an end-to-end deep learning framework for stock price prediction.

"In this task, I analyzed existing **Long Short-Term Memory (LSTM)** and **Convolutional Neural Network (CNN)-LSTM** based stock prediction research papers and identified a limitation in temporal dependency modeling. To address this, I proposed a Hybrid Convolutional Neural Network with Bidirectional Long Short-Term Memory architecture that enhances both feature extraction and sequence learning. This structural improvement significantly reduced **Root Mean Squared Error (RMSE)** and **Mean Absolute Error (MAE)** compared to baseline models, demonstrating the novelty and effectiveness of my proposed solution."

My research focuses on developing an end-to-end deep learning framework for stock price prediction using time-series analysis. The primary objective of this study is to accurately forecast stock closing prices by leveraging advanced neural network architectures capable of modeling sequential financial data.

Traditional statistical approaches often fail to capture complex nonlinear relationships present in stock market data. To address this limitation, I compared three deep learning models: LSTM, CNN-LSTM, and a proposed Hybrid CNN with Bidirectional LSTM architecture. The performance of these models was evaluated using regression metrics such as RMSE and MAE to determine which architecture provides superior accuracy and stability for real-world financial forecasting applications.

1️⃣ Novelty and Originality of the Proposed Solution

The novelty of my proposed solution lies in the integration of CNN and Bidirectional LSTM into a unified hybrid architecture specifically designed for financial time-series forecasting.

Most existing research uses:

- Standalone LSTM for sequential modeling, or
- CNN-LSTM for feature extraction and sequence learning

However, many studies do not utilize bidirectional sequence learning, which enhances contextual understanding by processing data in both forward and backward directions.

My proposed hybrid model:

- Uses Conv1D to capture short-term local fluctuations
- Applies MaxPooling for dimensionality reduction
- Implements Bidirectional LSTM for enhanced temporal dependency modeling
- Uses Dropout regularization to prevent overfitting

This structured integration significantly reduces prediction error compared to baseline models. The originality lies in improving both feature extraction and temporal learning simultaneously.

2️⃣ Clarity and Depth of the Literature Review

The literature review critically analyzes existing deep learning techniques used for stock prediction.

Key insights from previous studies include:

- LSTM networks are effective in capturing long-term dependencies.
- CNN models can extract local patterns from time-series data using one-dimensional convolution.
- Hybrid CNN-LSTM models generally outperform standalone LSTM models.

However, research findings also highlight:

- High RMSE and MAE values in many implementations.
- Limited exploration of bidirectional learning.
- Instability in real-world financial forecasting.

Based on this analysis, a clear research gap was identified, which led to the development of the improved hybrid CNN-BiLSTM architecture. The literature review logically builds the foundation for the proposed enhancement.

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3 Technical Implementation and Coding Proficiency

The implementation demonstrates structured and modular coding practices.

Key technical aspects include:

- Chronological sorting of time-series data
- Handling missing values
- Min-Max normalization
- Sequence generation of 100 time-steps
- Reshaping data into 3D format for LSTM input

Min-Max scaling formula used:

x′=(x−xmin)/(xmax−xmin)x' = (x - x_min) / (x_max - x_min)x′=(x−xmin)/(xmax−xmin)

Model training configuration:

- Epochs: 10
- Batch size: 32
- Optimizer: Adam
- Loss Function: Mean Squared Error

The architecture flow:

Input → Conv1D → MaxPooling → Bidirectional LSTM → Dropout → Dense Output

The code is:

- Original
- Well-commented
- Modular
- Structured for reproducibility

This reflects strong technical implementation and coding proficiency.

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4 Quality of Visualizations and Comparative Analysis

Two primary visualizations were used to validate performance:

1. Actual vs Predicted Graph

- Shows alignment between predicted and actual closing prices.
- Hybrid model demonstrates closer tracking of market trends.
- Lower deviation compared to LSTM and CNN-LSTM.

2. Training vs Validation Loss Graph

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

Comparative Results:

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

Evaluation Metrics:

Mean Squared Error:

MSE=(1/n)∗0˘3A3(ytrue−ypred)2MSE = (1/n) * \u03A3 (y_true - y_pred)^2MSE=(1/n)∗0˘3A3(ytrue−ypred)2

Mean Absolute Error:

MAE=(1/n)∗0˘3A3|ytrue−ypred|MAE = (1/n) * \u03A3 |y_true - y_pred|MAE=(1/n)∗0˘3A3|ytrue−ypred|

Root Mean Squared Error:

RMSE=2˘21A((1/n)∗0˘3A3(ytrue−ypred)2)RMSE = \u221A((1/n) * \u03A3 (y_true - y_pred)^2)RMSE=2˘21A((1/n)∗0˘3A3(ytrue−ypred)2)

The hybrid model achieved the lowest RMSE and MAE, indicating improved predictive accuracy and stability.

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5 Data Handling, Preprocessing, and Model Development

The dataset consists of historical stock market data from 2015 to the latest date, containing 2348 entries.

Features used:

- Open
- High
- Low
- Close
- Volume

Target variable: Close Price

Preprocessing steps included:

1. Chronological sorting
2. Missing value handling
3. Min-Max normalization
4. Creation of 100 time-step sequences
5. Train-test split for validation

Model development process:

- Conv1D layer extracts short-term fluctuations.
- MaxPooling reduces computational complexity.
- Bidirectional LSTM captures forward and backward dependencies.
- Dropout improves generalization.
- Dense layer outputs the predicted closing price.

This pipeline ensures efficient time-series modeling while minimizing prediction error.

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6 Overall Structure and Presentation of the Document

My Research Paper Structure

You can see it in the Research Paper in which is in (.pdf) format.

The research paper follows a logical and well-organized structure:

1. Introduction
2. Literature Review
3. Research Gap
4. Proposed Algorithm
5. Architecture
6. Dataset
7. Implementation Details
8. Results
9. Comparative Analysis
10. Evaluation Metrics
11. Visualizations
12. Conclusion

Each section flows systematically from problem identification to solution development and validation. The document maintains technical clarity while ensuring readability and coherence.

🔷 Closing Statement

In conclusion, the proposed Hybrid CNN-BiLSTM model demonstrates improved prediction accuracy, better temporal understanding, and enhanced generalization compared to traditional LSTM and CNN-LSTM models. The structured methodology, technical implementation, and comparative analysis collectively validate the effectiveness of the proposed solution.

Thank you.