Machine Learning for Stock Price Prediction

Project report submitted in partial fulfillment
of the requirements for the degree of

Bachelor of Technology
in
Computer Science Engineering

by

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CERTIFICATE

This is to certify that the project entitled "Machine Learning for Stock Price Prediction", submitted by Virender Kumar(21UEC144), Suman Kumar Singh (21UCC099), and Snehil Singh Solanki (21UCC097) in partial fulfillment of the requirement of degree in Bachelor of Technology (B. Tech), is a bonafide record of work carried out by them at the Department of Computer Science Engineering, The LNM Institute of Information Technology, Jaipur, (Rajasthan) India, during the academic session 2024-2025 under my supervision and guidance and the same has not been submitted elsewhere for the award of any other degree. In my/our opinion, this report is of standard required for the award of the degree of Bachelor of Technology (B. Tech).

Date	Adviser: Name of BTP Supervisor

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Abstract

The stock market is a complex system influenced by various factors such as economic conditions, company performance, and investor sentiment. This project aims to develop a model that can accurately predict stock price movements using historical data and technical analysis.

The application of machine learning for stock prediction has attracted much attention in recent years. Stock market analysis is crucial for investors and financial institutions to make informed decisions. As historical stock market data and advances in machine learning algorithms increase, the interest in using machine learning in stock analysis is growing. This study provides an in-depth stock market analysis using machine learning, focusing on applying various machine learning techniques and methods. Research begins with data collection, where historical stock market data is collected from financial databases, APIs, and online surveys. The data are pre-processed to handle missing values and outliers and to generate relevant features for analysis. Feature selection and dimensionality reduction techniques are used to reduce the complexity of the dataset. The study also uses advanced machine learning techniques, such as deep learning, including long-term memory (LSTM) networks, to analyze stock markets.

The results demonstrate how convolutional and sequential learning techniques provide reliable stock market predictions. Compared to standalone LSTM and TCN models, the experimental findings show that the suggested models—especially the hybrid architectures—achieve better prediction accuracy and efficiency.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Introduction

This project proposes a novel approach for stock market prediction using long short-term memory (LSTM), Temporal Convolutional Network(TCN), and two hybrid models, one is Convolutional Neural Network(CNN) + Long Short-Term Memory(LSTM), and another is Convolutional Neural Network(CNN) + Temporal Convolutional Network (TCN). These models leverage the strengths of deep learning to process sequential data, making them well-suited for time series prediction tasks such as stock market prediction.

The LSTM, TCN, and hybrid models are trained and tested on diverse stock tickers, and their prediction results are compared to a baseline model. The hybrid models combine the spatial feature extraction capability of CNNs with the sequential processing power of LSTM and TCN architectures, allowing for more robust stock market predictions.

LSTM is a recurrent neural network (RNN) capable of capturing long-term dependencies in sequential data, making it highly effective for time series prediction tasks. TCN, on the other hand, uses causal convolution and dilated layers to process sequences efficiently, providing faster training and better handling of long-range dependencies compared to traditional RNNs.

1.2 Need of Stock Prediction

Stock market predictions play a critical role in the financial ecosystem, benefiting various stakeholders in multiple ways:

1. **Informed Investment Decisions:** Stock predictions provide valuable insights that enable investors to make strategic decisions regarding buying, holding, or selling stocks.

For example, understanding the future trajectory of a company's performance helps investors align their portfolios with their financial goals.

2. **Risk Management:** Accurate stock market forecasts allow investors to identify potential risks and opportunities. For instance, if a market downturn is anticipated, investors can adjust their strategies to minimize exposure to volatile assets, thereby reducing potential losses.

3. **Trend and Pattern Analysis:** Predicting stock market movements helps analysts and experts uncover patterns and trends in market behaviour. This understanding can guide the development of effective trading strategies and broader market insights.

4. **Strategic Business Planning:** Businesses leverage stock market predictions for planning and decision-making. For instance, companies may analyze market trends to determine optimal investment opportunities, hiring plans, or strategic expansions. These forecasts also help businesses anticipate market conditions that could influence their growth.

5. **Market Sentiment Understanding:** Forecasts provide a snapshot of the overall health of the stock market, offering insights into economic trends and investor confidence. Such information is invaluable for traders and institutional investors who rely on market sentiment to optimize their strategies.

6. **Improved Financial Stability:** For regulators and policymakers, stock market predictions can assist in monitoring the market for potential instabilities or speculative bubbles, ensuring a more robust financial system.

1.3 Long Short Term Memory-LSTM

Among the various varieties of recurrent neural networks (RNNs), long short-term memory (LSTM) can store information from previous phases and be utilized to make predictions for the future. The Long Short-Term Memory (LSTM) based on the ”memory line” was beneficial in forecasting scenarios with long-term data because RNNs cannot store long-term memory. Memorizing previous stages can be accomplished in an LSTM using integrated gates with a memory line.[2][1][3]

In the below figure, every line represents an entire feature vector, from the output of one node to the inputs of others. The pink circles represent pointwise operations, like vector addition, while the yellow boxes are learned neural network layers. Lines merging denote concatenation, while a line forking denotes its content being copied and the copies going to different locations.

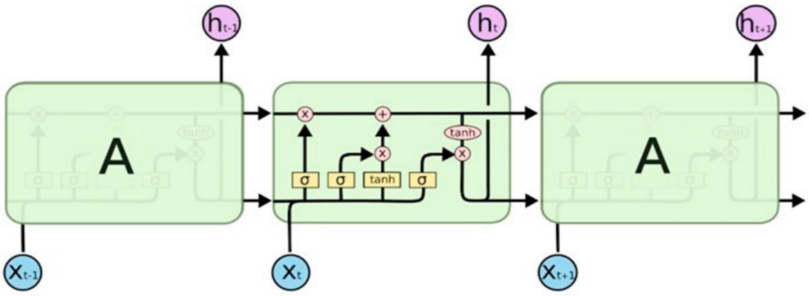

FIGURE 1.1: LSTM Model Diagram [1]

1.4 Temporal Convolutional Network-TCN

Temporal Convolutional Networks (TCNs) are deep learning models that handle sequence data. They are particularly effective for tasks involving time-series data, such as forecasting, anomaly detection, and sequence classification. TCNs leverage the power of convolutional neural networks (CNNs) and adapt them to sequence data, providing several advantages over traditional recurrent neural networks (RNNs) and long short-term memory (LSTM) networks.[1][4]

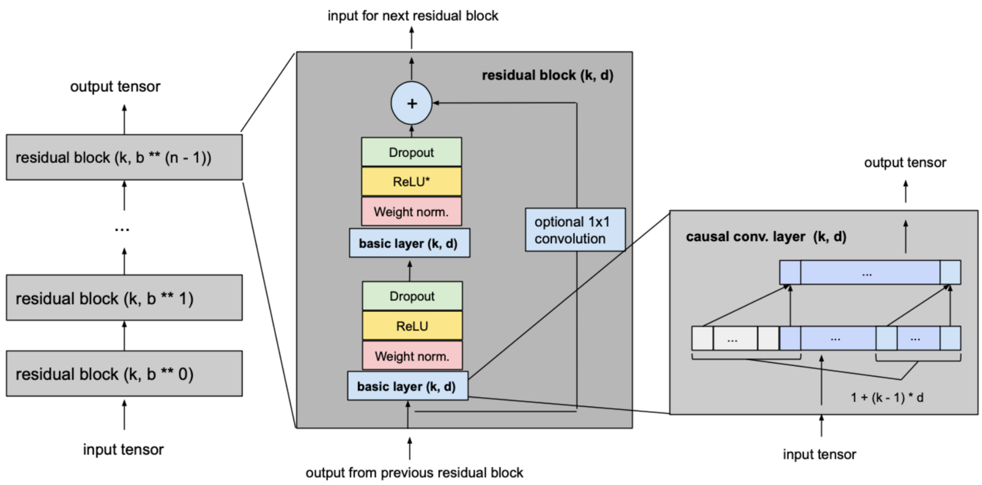

FIGURE 1.2: TCN Model Diagram

1.5 Convolutional Neural Network-CNN

CNN is a class of deep neural networks whose applications focus on image analytics. In detail, most CNNs have several convolution and pooling layers. Normally, convolution layers are responsible for extracting high-level features in the images through padding operation.[5]

This will pack information in a small field into a single feature rather than a grid of features. The pooling layer can help decrease the computational power required to process through the pooling operation, which divides the entire graph into several sub-segments and an extra feature for each segment.

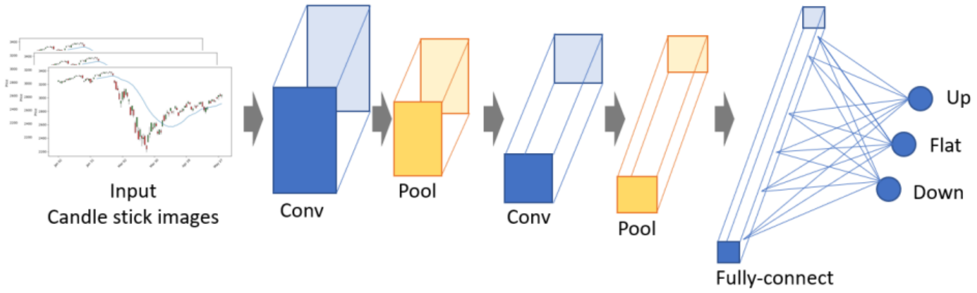

FIGURE 1.3: CNN Model Diagram

Chapter 2

Literature Review

Many researchers are drawn to the field of stock market forecasting. Using accurate stock price forecasts, investors can make better decisions about when to buy and sell stocks. In recent years, numerous scholars have examined machine learning techniques for stock price predictability. The primary goal of this study is to find the most effective machine learning methods for stock price prediction. The methodology employed to accomplish this goal is a review of twelve research publications on using machine learning and deep learning algorithms for stock price prediction. This study differs from the present one in that it focuses on two primary industries—banking and healthcare—instead of choosing articles randomly.
Regardless of the industry in which they are utilized, the study's findings demonstrate that restricted repetition units and long-term, short-term memory procedures yield the most excellent outcomes for most of the chosen books—significant restrictions on the research. As stock trading gains popularity, more people and organizations are actively participating in the stock market to make money, including hedge funds, investment businesses, and private investors. Numerous tactics have been created and put into practice, ranging from conventional techniques that employ technical and fundamental analysis to contemporary methods that use state-of-the-art technology. Determining the best approach is still challenging, though.

There are significant challenges in developing a successful strategy in the intricate and ever-changing stock market environment. To determine the most popular machine learning models or techniques for market forecasting, this article aims to summarise machine learning applications in the stock market. The study also seeks to determine the approach that predicts stock values with the highest accuracy. The most often used machine learning method for stock price prediction is the Support Vector Machine (SVM), according to a comprehensive literature assessment including quantitative and qualitative analyses. With an astounding accuracy of 99.58 per cent, Long Short-Term Memory (LSTM) is the machine learning method with the highest precision.

These results demonstrate how well LSTM predicts stock value with remarkable precision. The findings of this study offer essential information for creating successful trading strategies and further a thorough grasp of machine learning in the stock market. To enhance their stock market predictions and make wise investment choices, investors might employ the review's conclusion to suggest future research directions for machine learning to stock market forecasting, compiled in this literature survey. Research from a range of sources, including journals, conference proceedings, and theses, is included in the review. Artificial neural networks, support vector machines, decision trees, and time series analysis are some of the machine learning techniques used to predict stock markets. The paper also discusses the benefits and drawbacks of these techniques and how they are used in the stock market. The review's findings demonstrate that while machine learning can yield useful insights into the stock market, accuracy and robustness can still be enhanced. The review's conclusion suggests future research directions for the field.

The typical individual is interested in it because stock trading may be a profitable endeavour if done correctly. Forecasting stock prices are challenging and require a wealth of data regarding market shares and trends. Stock markets are dynamic and erratic by nature. Stock price movement is extremely unpredictable and challenging to observe. In the past, econometric, technical, and fundamental models were used to forecast stocks. Traditional analytical methodologies cannot properly handle the volume and complexity of data produced in today's marketplaces. The application of machine learning to stock valuation is growing in popularity.

Machine learning can assist in identifying patterns and trends that could indicate future changes in stock prices by analyzing big data sets using complex algorithms. Finding the relationship between stock prices and the outside world is another application of machine learning. Additionally, it can be used to determine when it would be best to purchase, sell, or hold onto stock. A machine learning algorithm can be used to estimate stock prices reliably. Additionally, it is employed to identify market irregularities like insider trading and market manipulation. Forecasting stock market prices has become a hot research topic for traders, investors, and traders. Investors in this forecasting activity want fast and real-time information to make prompt and precise decisions.

Most researchers have recently created algorithms forecasting a stock's price and average movement. The results, conclusions, research needs, and potential applications of each method are also covered. While deep learning makes predictions based on current stock market index values by training its past values, machine learning makes predictions based on current stock market index values by training its previous values in a timely and sequential sequence using an artificial neural network. .. artificial neural network-based sequential temporal ordering. Prices on the stock market fluctuate every second and are created in large quantities. People can make money or lose their savings in the intricate and challenging stock market system.

This study makes an effort to forecast how the stock market will evolve. Being able to predict how the stock market will move can be a big disadvantage. This research primarily employs machine learning approaches to examine various stock market-related factors to accomplish its purpose. By creating stock market prediction models from stock datasets, machine learning techniques have a proven track record of successfully extracting information. Forecasting the stock market may benefit from data mining of this data. The work aims to determine how successfully current changes—such as increases and decreases in the company's expenses—correlate with public sentiment conveyed by the company's tweets.

Chapter 3

Proposed Work

3.1 Dataset Description and Preparation

3.1.1 Source of data

The data for this project was sourced from Yahoo Finance, a reliable and widely used platform for accessing historical and real-time stock market data. We utilized the yfinance Python library to efficiently retrieve stock data for four major Indian companies listed in the Sensex: Reliance Industries (RELIANCE.NS), Tata Consultancy Services (TCS.NS), HDFC Bank (HDFCBANK.NS), and Infosys (INFY.NS).

The dataset forms the foundation for training and evaluating our predictive models. Using yfinance, we automated the data collection process, ensuring consistency and accuracy in the retrieved financial data.

3.1.2 Preprocessing

To prepare the raw stock data for analysis and modelling, we employed the following preprocessing steps:

1. **Data Cleaning:** Any missing or null values in the dataset were handled to maintain data integrity. Missing entries were interpolated or dropped based on their significance and occurrence.

2. **Normalization**The selected feature was scaled using the MinMaxScaler to normalize the data from 0 to 1. This step ensured that the model training process was not skewed due to variations in the scale of data values.

3. **Data Transformation**A look-back window of 60 days was used to create input sequences (X), where each sequence predicts the next stock price (y). This enabled the models to learn temporal dependencies effectively.

```
def preprocess_data(data, look_back=60):
    scaler = MinMaxScaler(feature_range=(0, 1))
    scaled_data = scaler.fit_transform(data[['Open']])

    X, y = [], []
    for i in range(look_back, len(scaled_data)):
        X.append(scaled_data[i-look_back:i, 0])
        y.append(scaled_data[i, 0])

    X, y = np.array(X), np.array(y)
    X = np.reshape(X, (X.shape[0], X.shape[1], 1))

    return X, y, scaler
```

FIGURE 3.1: Lookback variable

3.2 Feature Engineering

Feature engineering is a critical step in preparing data for machine learning models, as it helps improve the accuracy and efficiency of predictions by creating features that better capture the underlying patterns in the data. In this project, we focused on the Open price of each stock as the primary feature for prediction.

3.3 Evaluation Metrics

Evaluation metrics play a pivotal role in assessing the performance of predictive models. They help quantify the model's accuracy, reliability, and generalizability. The following metrics were used to evaluate the performance of our LSTM-based stock price prediction model, as implemented in the code:

3.3.1 Mean Absolute Error (MAE)

Measures the average magnitude of errors in predictions without considering their direction. Provides a straightforward interpretation of error magnitude in the same unit as the stock price.
Lower values indicate better performance.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

FIGURE 3.2: Mean Absolute Error

y$_i = ActualValues$
$y_i^{'} = PredictedValues$
$n = numberofdatapoints$

3.3.2 Mean Squared Error (MSE)

Measures the average squared differences between actual and predicted values. Penalizes larger errors more than smaller ones, making it sensitive to outliers.
Smaller values indicate better model accuracy.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

FIGURE 3.3: Mean Squared Error

y$_i = ActualValues$
$y_i^{'} = PredictedValues$
$n = numberofdatapoints$

3.3.3 Root Mean Squared Error (RMSE)

The square root of MSE represents the model's error in the same unit as the stock price. A more interpretable error measure compared to MSE.
Lower values indicate higher accuracy.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

FIGURE 3.4: Root Mean Squared Error

y$_i = ActualValues$
$y_i^{'} = PredictedValues$
$n = numberofdatapoints$

3.3.4 R² Score (Coefficient of Determination)

Represents the proportion of variance in the actual data that the model explains.
Higher values suggest the model performs well in capturing data trends.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

FIGURE 3.5: R² Score

y$_i = ActualValues$
$y_i^{'} = PredictedValues$
$n = numberofdatapoints$
$y^{-} = Meanofactualvalues$

3.3.5 Directional Accuracy (DA)

Measures the percentage of times the model correctly predicts the direction of price movement (upward or downward). Particularly relevant for stock price prediction, as identifying the correct trend is often more valuable than precise price predictions.
Higher percentages indicate better performance.

$$\mathrm{DA}(\%) = \frac{\text{Number of Correct Predictions in Direction}}{\text{Total Predictions}} \times 100$$

FIGURE 3.6: Directional Accuracy

3.4 Advantages of Hybrid Models

Hybrid models, which combine different machine learning or deep learning architectures, leverage the strengths of individual components to address the limitations of standalone models. In stock price prediction, hybrid models like CNN-LSTM or CNN-TCN provide significant advantages over singular approaches.

3.4.1 Enhanced Feature Extraction

Convolutional Neural Networks (CNNs) excel at extracting spatial features, while models like LSTM or TCN handle temporal dependencies effectively. These hybrid models allow us to understand local patterns (e.g., short-term fluctuations) and long-term trends (e.g., seasonal movements).
This ensures that the model captures essential price patterns, volatility, and trends for stock data.

3.4.2 Improved Predictive Accuracy

Hybrid models synergize their components' strengths to achieve better prediction accuracy. For instance, while LSTMs are adept at capturing sequential dependencies, CNNs filter noise and extract key features. This results in models that are both robust to noise and adept at understanding sequential patterns, leading to reduced errors in forecasting.

3.4.3 Robustness to Non-Stationary Data

Financial data is often non-stationary, meaning its statistical properties change over time. With their ability to adapt to complex patterns, hybrid models are better equipped to handle such dynamic datasets.
For example, CNNs can detect sudden trends, while LSTMs or TCNs track how these changes evolve over time.

3.4.4 Improved Trend Prediction

In stock markets, predicting the direction of price movements is often more crucial than predicting the exact price. Hybrid models combine local pattern recognition with sequence modelling, improving directional accuracy.
This makes hybrid models valuable for applications like algorithmic trading and risk assessment.

Chapter 4

Simulation and Results

The outcomes of our research demonstrate the performance of the hybrid deep learning models implemented for stock price and volume prediction. The results are validated through visual and tabular representations and a comparative discussion based on established evaluation metrics.

4.1 Experimental Setup

The models were implemented using TensorFlow and Keras libraries in Python. The datasets obtained from Yahoo Finance include the daily stock prices of four Sensex-listed companies: RELIANCE, TCS, HDFCBANK, and INFOSYS.

Each model was evaluated for predicting the following metrics:

1. **Opening Price**
2. **Closing Price**
3. **Volume**
4. **Combined Closing Price + Volume**

We trained and tested the following models:

1. **LSTM**
2. **TCN**
3. **CNN+LSTM**

4. **CNN+TCN**

Each model was run for 20 epochs with a batch size of 32. The performance was assessed on both predictive accuracy and directional accuracy.

4.2 Visual Representation of Predictions

The figures below illustrate the selected companies' predicted vs. actual opening prices using all four models. These diagrams clearly compare how each model captures the trends and patterns in stock price movements.

4.2.1 LSTM Model

4.2.1.1 TCS-LSTM Opening Price Prediction

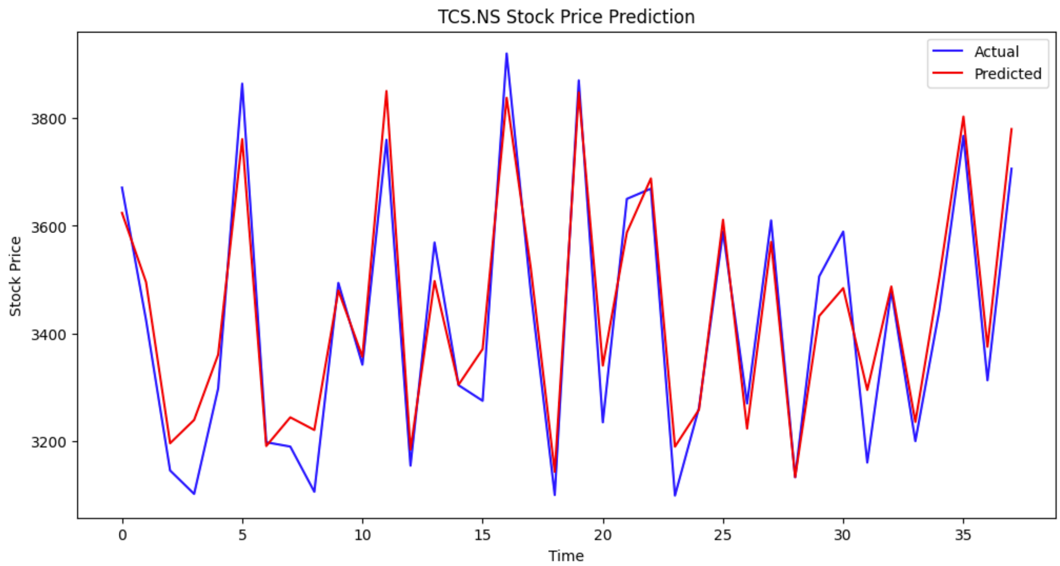

FIGURE 4.1: TCS Opening Price Actual vs Prediction Using LSTM

4.2.1.2 HDFC-LSTM Opening Price Prediction

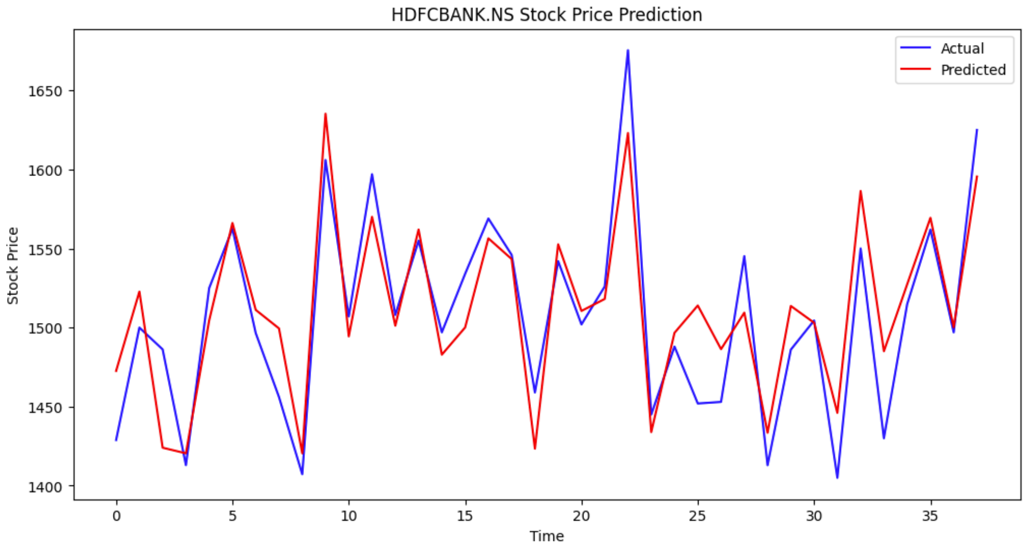

FIGURE 4.2: HDFC Opening Price Actual vs Prediction Using LSTM

4.2.2 TCN Model

4.2.2.1 TCS-TCN Opening Price Prediction

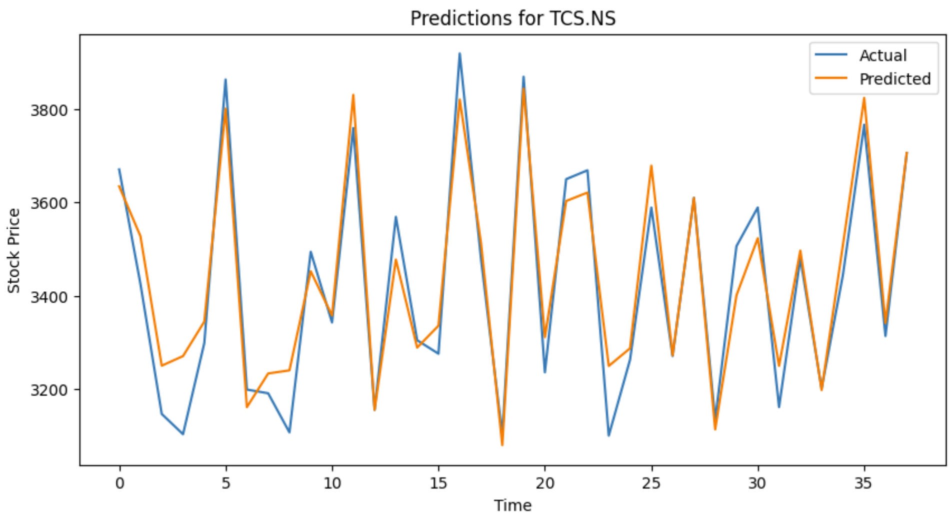

FIGURE 4.3: TCS Opening Price Actual vs Prediction Using TCN

4.2.2.2 HDFC-TCN Opening Price Prediction

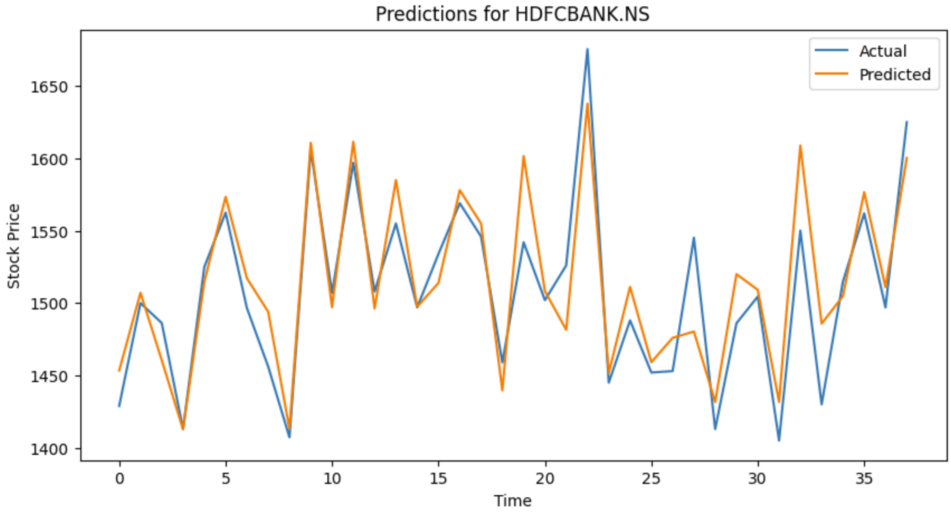

FIGURE 4.4: HDFC Opening Price Actual vs Prediction Using TCN

4.2.3 CNN+LSTM Model

4.2.3.1 TCS-CNN+LSTM Opening Price Prediction

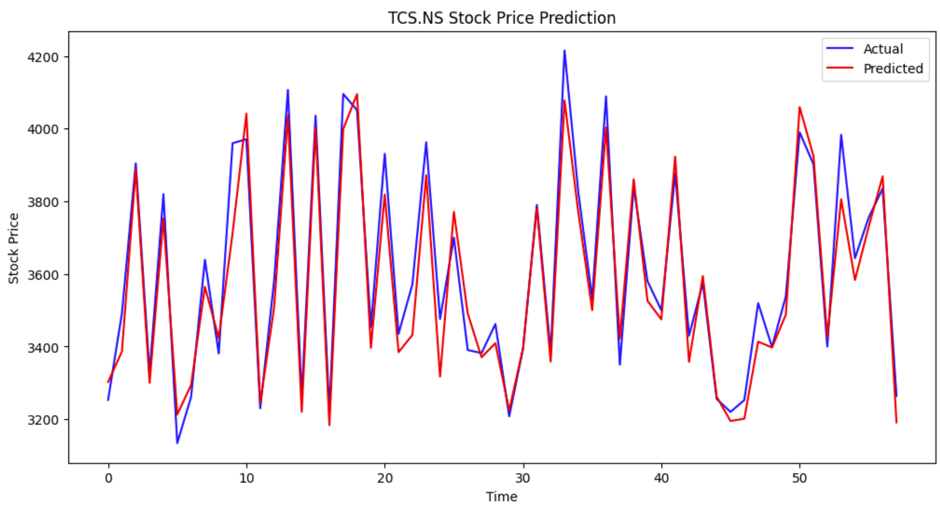

FIGURE 4.5: TCS Opening Price Actual vs Prediction Using CNN+LSTM

4.2.3.2 HDFC-CNN+LSTM Opening Price Prediction

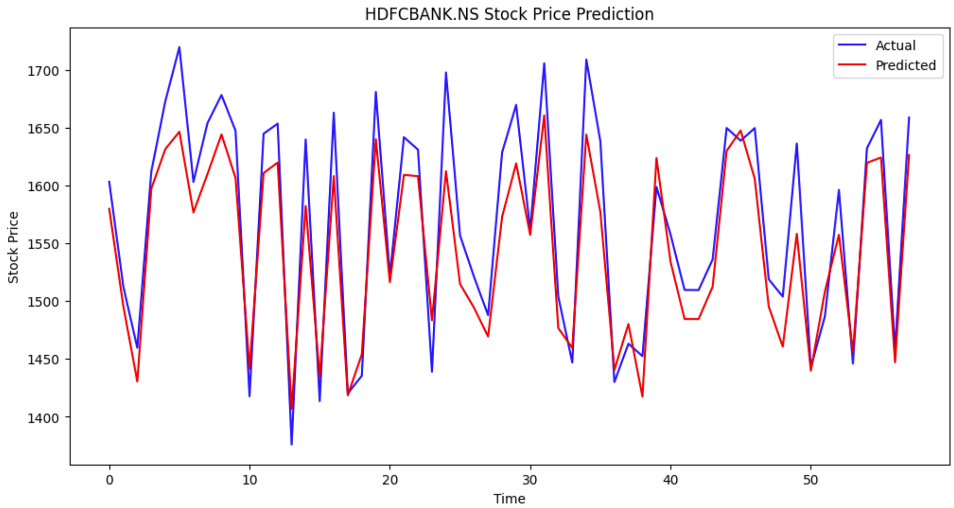

FIGURE 4.6: HDFC Opening Price Actual vs Prediction Using CNN+LSTM

4.2.4 CNN+TCN Model

4.2.4.1 TCS-CNN+TCN Opening Price Prediction

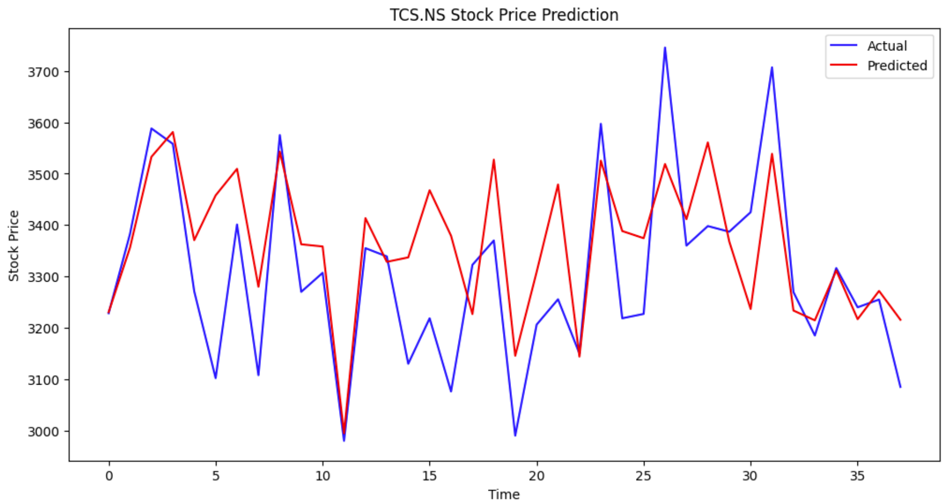

FIGURE 4.7: TCS Opening Price Actual vs Prediction Using CNN+TCN

4.2.4.2 HDFC-CNN+TCN Opening Price Prediction

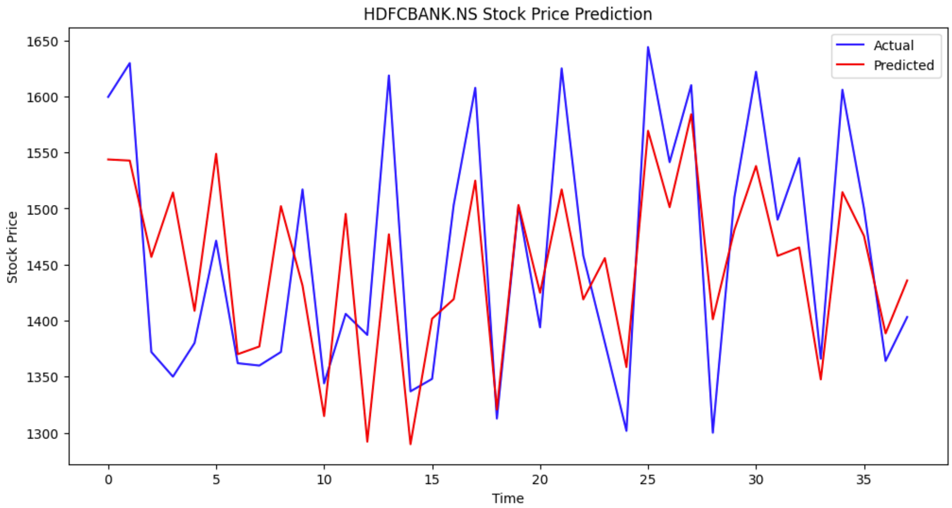

FIGURE 4.8: HDFC Opening Price Actual vs Prediction Using CNN+TCN

4.3 Tabular Representation of Results

We generated predictions for the four metrics across all companies to evaluate the models' accuracy. The tables below summarize the results, including predicted and actual values and corresponding errors.

4.3.1 Performance Metrics for LSTM Model

4.3.1.1 Opening Price

The performance metrics for predicting the Opening price of stocks using the LSTM model are summarized below.

Company/Properties	**MAE**	**MSE**	**RMSE**	**DA (%)**	**R^2 Score**
Reliance	2.7×10^1	1.2×10^3	3.4×10^1	9.2×10^1	8.9×10^{-1}
TCS	5.6×10^1	4.5×10^3	6.7×10^1	9.2×10^1	9.2×10^{-1}
HDFC	2.3×10^1	8.3×10^2	2.9×10^1	9.2×10^1	7.9×10^{-1}
INFY	3.7×10^1	2.1×10^3	4.5×10^1	9.2×10^1	9.2×10^{-1}

TABLE 4.1: Performance Metrics for LSTM Model in Predicting Opening Prices

4.3.1.2 Closing Price

The performance metrics for predicting the closing price of stocks using the LSTM model are summarized below.

Company/Properties	**MAE**	**MSE**	**RMSE**	**DA (%)**	**R^2 Score**
Reliance	2.7×10^1	1.3×10^3	3.6×10^1	9.5×10^1	8.8×10^{-1}
TCS	6.5×10^1	6.2×10^3	7.9×10^1	9.5×10^1	9.0×10^{-1}
HDFC	2.6×10^1	1.0×10^3	3.2×10^1	9.2×10^1	7.5×10^{-1}
INFY	3.3×10^1	1.6×10^3	4.1×10^1	9.5×10^1	9.4×10^{-1}

TABLE 4.2: Performance Metrics for LSTM Model: Closing Price

4.3.1.3 Volume

The performance metrics for predicting the volume of stocks using the LSTM model are summarized below.

Company/Properties	**MAE**	**MSE**	**RMSE**	**DA (%)**	**R^2 Score**
Reliance	5.1×10^6	5.1×10^{13}	7.2×10^6	6.2×10^1	9.1×10^{-2}
TCS	7.8×10^5	1.3×10^{12}	1.1×10^6	5.7×10^1	1.3×10^{-1}
HDFC	2.1×10^6	7.8×10^{12}	2.8×10^6	6.5×10^1	3.9×10^{-1}
INFY	2.0×10^6	1.1×10^{13}	3.3×10^6	5.1×10^1	1.5×10^{-1}

TABLE 4.3: Performance Metrics for LSTM Model: Volume

4.3.1.4 Closing Price + Volume

The performance metrics for predicting both closing price and volume using the LSTM model are summarized below.

Closing Price:

Company/Properties	**MAE**	**MSE**	**RMSE**	**DA (%)**	**R^2 Score**
Reliance	2.7×10^1	1.2×10^3	3.5×10^1	9.5×10^1	8.8×10^{-1}
TCS	6.1×10^1	5.5×10^3	7.4×10^1	9.5×10^1	9.1×10^{-1}
HDFC	2.6×10^1	1.0×10^3	3.2×10^1	9.2×10^1	7.5×10^{-1}
INFY	2.8×10^1	1.3×10^3	3.6×10^1	9.5×10^1	9.5×10^{-1}

TABLE 4.4: Performance Metrics for LSTM Model: Closing Price (Combined with Volume)

Volume:

Company/Properties	MAE	MSE	RMSE	DA (%)	R^2 Score
Reliance	5.2×10^{6}	5.6×10^{13}	7.5×10^{6}	5.9×10^{1}	1.0×10^{-2}
TCS	7.4×10^{5}	1.2×10^{12}	1.1×10^{6}	6.8×10^{1}	1.7×10^{-1}
HDFC	2.1×10^{6}	7.6×10^{12}	2.8×10^{6}	6.2×10^{1}	4.0×10^{-1}
INFY	2.0×10^{6}	1.1×10^{13}	3.3×10^{6}	5.9×10^{1}	1.6×10^{-1}

TABLE 4.5: Performance Metrics for LSTM Model: Volume (Combined with Closing Price)

4.3.2 Performance Metrics for TCN Model

4.3.2.1 Opening Price

The performance metrics for predicting the opening price of stocks using the TCN model are summarized below.

Company/Properties	MAE	MSE	RMSE	DA (%)	R^2 Score
Reliance	2.2×10^{1}	8.5×10^{2}	2.9×10^{1}	9.2×10^{1}	9.2×10^{-1}
TCS	5.5×10^{1}	4.8×10^{3}	6.9×10^{1}	8.9×10^{1}	9.2×10^{-1}
HDFC	2.1×10^{1}	7.4×10^{2}	2.7×10^{1}	9.5×10^{1}	8.1×10^{-1}
INFY	3.0×10^{1}	1.5×10^{3}	3.9×10^{1}	8.9×10^{1}	9.4×10^{-1}

TABLE 4.6: Performance Metrics for TCN Model: Opening Price

4.3.2.2 Closing Price

The performance metrics for predicting the closing price of stocks using the TCN model are summarized below.

Company/Properties	MAE	MSE	RMSE	DA (%)	R^2 Score
Reliance	2.6×10^{1}	1.0×10^{3}	3.2×10^{1}	9.5×10^{1}	9.0×10^{-1}
TCS	4.2×10^{1}	2.6×10^{3}	5.1×10^{1}	9.5×10^{1}	9.6×10^{-1}
HDFC	2.5×10^{1}	8.8×10^{2}	3.0×10^{1}	9.2×10^{1}	7.8×10^{-1}
INFY	6.1×10^{1}	5.0×10^{3}	7.1×10^{1}	9.5×10^{1}	8.1×10^{-1}

TABLE 4.7: Performance Metrics for TCN Model: Closing Price

4.3.2.3 Volume

The performance metrics for predicting the volume of stocks using the TCN model are summarized below.

Company/Properties	MAE	MSE	RMSE	DA (%)	R^2 Score
Reliance	6.0×10^6	6.3×10^{13}	7.9×10^6	6.5×10^1	-1.1×10^{-1}
TCS	8.5×10^5	1.9×10^{12}	1.4×10^6	5.7×10^1	-3.0×10^{-1}
HDFC	2.9×10^6	1.5×10^{13}	3.9×10^6	7.6×10^1	-1.9×10^{-1}
INFY	2.3×10^6	1.2×10^{13}	3.4×10^6	5.1×10^1	9.6×10^{-2}

TABLE 4.8: Performance Metrics for TCN Model: Volume

4.3.2.4 Closing Price + Volume

The performance metrics for predicting both closing price and volume using the TCN model are summarized below.

Closing Price:

Company/Properties	MAE	MSE	RMSE	DA (%)	R^2 Score
Reliance	2.8×10^1	1.2×10^3	3.4×10^1	9.2×10^1	9.1×10^{-1}
TCS	8.7×10^1	1.1×10^4	1.0×10^2	7.6×10^1	7.9×10^{-1}
HDFC	3.3×10^1	1.9×10^3	4.3×10^1	8.1×10^1	6.4×10^{-1}
INFY	3.1×10^1	1.6×10^3	4.0×10^1	8.9×10^1	9.4×10^{-1}

TABLE 4.9: Performance Metrics for TCN Model: Closing Price (Combined with Volume)

Volume:

Company/Properties	MAE	MSE	RMSE	DA (%)	R^2 Score
Reliance	6.2×10^6	6.3×10^{13}	7.9×10^6	5.7×10^1	-3.3×10^{-1}
TCS	1.2×10^6	2.0×10^{12}	1.4×10^6	6.8×10^1	-2.5×10^{-1}
HDFC	3.0×10^6	1.7×10^{13}	4.1×10^6	8.4×10^1	-1.0×10^{-1}
INFY	2.2×10^6	1.7×10^{13}	4.1×10^6	7.3×10^1	1.2×10^{-1}

TABLE 4.10: Performance Metrics for TCN Model: Volume (Combined with Closing Price)

4.3.3 Performance Metrics for CNN+LSTM Model

4.3.3.1 Opening Price

The performance metrics for predicting the opening price of stocks using the CNN + LSTM model are summarized below.

Company/Properties	**MAE**	**MSE**	**RMSE**	**DA (%)**	**R^2 Score**
Reliance	1.7×10^1	4.5×10^2	2.1×10^1	9.5×10^1	9.6×10^{-1}
TCS	4.5×10^1	3.2×10^3	5.7×10^1	8.6×10^1	9.5×10^{-1}
HDFC	2.0×10^1	6.2×10^2	2.5×10^1	9.2×10^1	8.4×10^{-1}
INFY	2.2×10^1	1.2×10^3	3.5×10^1	9.5×10^1	9.5×10^{-1}

TABLE 4.11: Performance Metrics for CNN + LSTM Model: Opening Price

4.3.3.2 Closing Price

The performance metrics for predicting the closing price of stocks using the CNN + LSTM model are summarized below.

Company/Properties	**MAE**	**MSE**	**RMSE**	**DA (%)**	**R^2 Score**
Reliance	1.7×10^1	4.7×10^2	2.2×10^1	9.5×10^1	9.5×10^{-1}
TCS	4.4×10^1	3.1×10^3	5.6×10^1	8.9×10^1	9.5×10^{-1}
HDFC	2.0×10^1	6.4×10^2	2.5×10^1	9.5×10^1	8.4×10^{-1}
INFY	2.1×10^1	8.4×10^2	2.9×10^1	9.2×10^1	9.7×10^{-1}

TABLE 4.12: Performance Metrics for CNN + LSTM Model: Closing Price

4.3.3.3 Volume

The performance metrics for predicting the volume of stocks using the CNN + LSTM model are summarized below.

Company/Properties	**MAE**	**MSE**	**RMSE**	**DA (%)**	**R^2 Score**
Reliance	5.3×10^6	5.9×10^{13}	7.7×10^6	7.0×10^1	-4.1×10^{-2}
TCS	7.2×10^5	1.1×10^{12}	1.0×10^6	7.3×10^1	2.7×10^{-1}
HDFC	2.2×10^6	8.8×10^{12}	3.0×10^6	6.5×10^1	3.1×10^{-1}
INFY	1.7×10^6	1.1×10^{13}	3.3×10^6	6.5×10^1	1.6×10^{-1}

TABLE 4.13: Performance Metrics for CNN + LSTM Model: Volume

4.3.3.4 Closing Price + Volume

The performance metrics for predicting both closing price and volume using the CNN + LSTM model are summarized below.

Closing Price:
Volume:

Company/Properties	MAE	MSE	RMSE	DA (%)	R^2 Score
Reliance	3.9×10^1	2.8×10^3	5.3×10^1	9.2×10^1	7.3×10^{-1}
TCS	2.1×10^2	6.1×10^4	2.5×10^2	5.9×10^1	-3.0×10^{-2}
HDFC	3.9×10^1	2.7×10^3	5.2×10^1	6.8×10^1	3.4×10^{-1}
INFY	1.2×10^2	2.0×10^4	1.4×10^2	8.1×10^1	2.4×10^{-1}

TABLE 4.14: Performance Metrics for CNN + LSTM Model: Closing Price (Combined with Volume)

Company/Properties	MAE	MSE	RMSE	DA (%)	R^2 Score
Reliance	5.6×10^6	6.2×10^{13}	7.9×10^6	5.4×10^1	-1.0×10^{-1}
TCS	7.9×10^5	1.4×10^{12}	1.2×10^6	7.0×10^1	2.0×10^{-2}
HDFC	2.3×10^6	8.3×10^{12}	2.9×10^6	5.7×10^1	3.5×10^{-1}
INFY	2.2×10^6	1.3×10^{13}	3.6×10^6	5.4×10^1	3.0×10^{-2}

TABLE 4.15: Performance Metrics for CNN + LSTM Model: Volume (Combined with Closing Price)

4.3.4 Performance Metrics for CNN+TCN Model

4.3.4.1 Opening Price

The performance metrics for predicting the opening price of stocks using the CNN + TCN model are summarized below.

Company/Properties	MAE	MSE	RMSE	DA (%)	R^2 Score
Reliance	2.4×10^1	9.9×10^2	3.1×10^1	8.6×10^1	9.2×10^{-1}
TCS	7.7×10^1	1.2×10^4	1.1×10^2	8.9×10^1	7.7×10^{-1}
HDFC	4.1×10^1	3.1×10^3	5.6×10^1	7.6×10^1	4.4×10^{-1}
INFY	3.9×10^1	2.4×10^3	4.9×10^1	8.6×10^1	9.2×10^{-1}

TABLE 4.16: Performance Metrics for CNN + TCN Model: Opening Price

4.3.4.2 Closing Price

The performance metrics for predicting the closing price of stocks using the CNN + TCN model are summarized below.

Company/Properties	MAE	MSE	RMSE	DA (%)	R^2 Score
Reliance	3.0×10^1	1.3×10^3	3.5×10^1	8.1×10^1	5.6×10^{-1}
TCS	1.1×10^2	1.9×10^4	1.4×10^2	8.9×10^1	3.5×10^{-1}
HDFC	3.9×10^1	2.1×10^3	4.6×10^1	9.2×10^1	8.3×10^{-1}
INFY	5.5×10^1	4.5×10^3	6.7×10^1	7.3×10^1	4.5×10^{-1}

TABLE 4.17: Performance Metrics for CNN + TCN Model: Closing Price

4.3.4.3 Volume

The performance metrics for predicting the volume of stocks using the CNN + TCN model are summarized below.

Company/Properties	**MAE**	**MSE**	**RMSE**	**DA (%)**	**R^2 Score**
Reliance	9.7×10^6	2.1×10^{12}	1.5×10^7	6.8×10^1	-2.7
TCS	2.1×10^6	6.7×10^{12}	2.6×10^6	4.9×10^1	-3.6
HDFC	2.8×10^6	1.4×10^{13}	3.7×10^6	6.5×10^1	-1.0×10^{-1}
INFY	4.5×10^6	3.4×10^{13}	5.8×10^6	4.9×10^1	-1.6

TABLE 4.18: Performance Metrics for CNN + TCN Model: Volume

4.3.4.4 Closing Price + Volume

The performance metrics for predicting both closing price and volume using the CNN + TCN model are summarized below.

Closing Price:

Company/Properties	**MAE**	**MSE**	**RMSE**	**DA (%)**	**R^2 Score**
Reliance	5.5×10^1	5.2×10^3	7.2×10^1	8.9×10^1	5.8×10^{-1}
TCS	1.3×10^2	2.7×10^4	1.6×10^2	7.8×10^1	4.8×10^{-1}
HDFC	5.0×10^1	4.0×10^3	6.3×10^1	6.8×10^1	2.1×10^{-1}
INFY	8.1×10^1	9.8×10^3	9.9×10^1	7.3×10^1	6.5×10^{-1}

TABLE 4.19: Performance Metrics for CNN + TCN Model: Closing Price (Combined with Volume)

Volume:

Company/Properties	**MAE**	**MSE**	**RMSE**	**DA (%)**	**R^2 Score**
Reliance	1.3×10^7	2.9×10^{14}	1.7×10^7	5.1×10^1	-5.2
TCS	1.3×10^6	2.5×10^{12}	1.6×10^6	6.2×10^1	-5.6×10^{-1}
HDFC	3.5×10^6	1.9×10^{13}	4.3×10^6	6.8×10^1	-2.5×10^{-1}
INFY	3.3×10^6	2.2×10^{13}	4.7×10^6	4.9×10^1	-1.6×10^{-1}

TABLE 4.20: Performance Metrics for CNN + TCN Model: Volume (Combined with Closing Price)

Chapter 5

Conclusions and Future Work

5.1 Conclusion

This study explored the potential of advanced machine learning models—LSTM, TCN, and hybrid CNN-based architectures—for predicting stock prices and volumes. The findings demonstrated that hybrid models like CNN+LSTM outperformed standalone models in accuracy and directional prediction, making them more suitable for complex, non-linear financial data. The hybrid models effectively leveraged the strengths of CNN for feature extraction and LSTM or TCN for capturing temporal dependencies, providing robust predictions even for volatile and non-stationary datasets.

The evaluation metrics indicated that CNN+LSTM models provided the best balance between prediction accuracy and computational efficiency, while CNN+TCN showed limitations in handling noisy volume data. However, all models contributed to a deeper understanding of machine learning's capabilities in financial forecasting, with notable implications for informed investment decisions and risk management.

5.2 Future Work

While this research achieved promising results, there are several avenues for improvement and expansion:

Enhanced Dataset Utilization Incorporating external datasets such as economic indicators, news sentiment analysis, and social media trends can further refine prediction accuracy. These datasets can provide a more comprehensive view of market dynamics.

Real-Time Implementation: Transitioning from static historical data to real-time stock prediction systems can significantly enhance practical usability. Future efforts could focus on optimizing these models for live-streaming data.

Exploration of Advanced Architectures: Emerging architectures, such as Transformer-based models or hybrid attention mechanisms, could be explored for their ability to handle long-range dependencies effectively in financial time-series data.

Sector-Specific Models: Developing models tailored to specific sectors, such as technology or healthcare, can improve the granularity and relevance of predictions, benefiting sector-specific stakeholders.

Integration with Automated Trading Systems: Integrating predictive models into algorithmic trading platforms would enable automated decision-making, enhancing trading strategies and financial returns.

Robustness to Market Anomalies: Future studies should focus on improving model robustness against sudden market shifts or anomalies caused by economic crises or geopolitical instability.

Explainability and Interpretability: Enhancing the interpretability of hybrid models will be crucial for gaining the trust of financial analysts and investors. Techniques like SHAP or LIME could be integrated to provide insights into the models' decision-making processes.

By addressing these areas, future research can expand the applicability of machine learning in financial markets, providing tools that are more accurate but also practical and reliable for real-world scenarios.

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