Stock market prediction and forecasting using Tesla stocks

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Abstract

Predicting stock prices has long been a central focus in financial research, as understanding market behavior and trends can significantly improve investment decisions. From this paper, we focus on forecasting Tesla stock prices using the "Historical Tesla Stocks" dataset, aiming to build models that deliver accurate and timely predictions. Given the fast-paced and data-heavy nature of the stock market, making informed decisions is challenging without reliable forecasting tools. To address this, we compare various deep learning techniques, including Bi-directional Long Short-Term Memory (BiLSTM), Convolutional Neural Networks (CNN), and a hybrid model called BiLSTM-MTRAN-TCN. This hybrid architecture combines the strengths of BiLSTM for sequence learning, a Transformer for capturing long-range dependencies, and Temporal Convolutional Networks (TCN) for identifying short-term patterns. While Transformers are powerful for understanding global context, they sometimes fall short in capturing sequence dynamics— something our model overcomes by blending these methods. By leveraging these advanced techniques, our goal is to provide investors and analysts with more accurate insights into market trends, helping them make smarter and more confident financial decisions.

Index terms: - BiLSTM-MTRAN-TCN, Transformers, financial research, global context.

1.Introduction

Stock market forecasting is an important field of financial studies that seeks to predict future directions of stock prices using past trends and economic variables [1]. The stock market is a highly dynamic and intricate environment where investors earn profits or incur losses depending on their ability to forecast trends accurately [2]. Due to stock price volatility, making informed decisions in this field is challenging. Since stock market data is produced in large quantities and fluctuates continuously, forecasting future trends requires sophisticated techniques capable of processing and analyzing extensive datasets effectively [3].

This paper utilizes the dataset "Historical Tesla Stocks" to develop stock price forecast models for Tesla products and accessories [4]. Through an analysis of past price trends and economic patterns, the research aims to construct models that provide insightful analysis of future stock price movements [5]. Machine learning algorithms such as Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), a hybrid CNN-LSTM model and an improved transformer model (MTRAN-TCN) are explored to evaluate their effectiveness in forecasting stock prices

[6]These models are designed to handle sequential financial data and recognize patterns that influence price movements [7]

The performance of these models is measured using the Mean Squared Error (MSE), a widely used performance metric that calculates the average difference between forecasted and actual stock prices [8]. A lower MSE value indicates better prediction accuracy, meaning the model can estimate future stock prices more precisely [9]. By comparing the performance of different models, this paper identifies the most effective approach for stock market prediction [10].

This paper emphasizes deep learning models to forecast stock market trends using historical Tesla stock prices and to explore key factors influencing stock price movements and compare the performance of three models: CNN-LSTM, CNN-BiLSTM[11], and the proposed BiLSTM-MTRAN- TCN. The effectiveness of each model is assessed using Mean Squared Error (MSE) as the primary evaluation metric [12]. By identifying the most accurate model, this research provides valuable insights that can assist analysts and investors in making more informed financial decisions [13][14].

The aim of this model demonstrates that ML models can provide valuable insights into stock trends, helping investors and financial analysts make informed trading decisions. Since stock prices are influenced by various factors such as market trends, economic conditions, and investor sentiment, having accurate predictive models can significantly enhance decision-making in financial markets. This paper highlights the importance of using advanced machine learning techniques for stock price prediction and contributes to the ongoing research in financial forecasting by showcasing the potential of LSTM, CNN, CNN-LSTM and transformer models in stock market analysis.

2.Literature Survey

The financial marketplace is noisy, non-parametric dynamic and there are mainly two types of forecasting techniques: Technical analysis technique and machine learning techniques. The conventional econometric techniques or equations with parameters aren't appropriate for reviewing complicated large dimensional and noisy financial data.

Over the course of time, researchers have explored a wide range of approaches to predict stock market movements. Traditional models like ARIMA and Hidden Markov Models have been widely used, but newer methods such as Artificial Neural Networks (ANN) and Recurrent Neural Networks (RNN) have gained traction for their ability to learn complex patterns. As Rao et al. [15] pointed out, no single model fits all situations—it really depends on how volatile the market is and what kind of trends are present in the data.

Among deep learning techniques, LSTM networks have shown particularly strong performance. Phuoc et al. [16] used LSTM models on the Vietnamese stock market and reached a 93% accuracy using indicators like SMA, MACD, and RSI. Gupta et al. [19] also found that LSTM outperformed other models like CNN, RNN, ARIMA, and even basic moving averages, especially in terms of error

reduction and trend recognition. These findings highlight how powerful LSTM can be when it comes to forecasting time-series financial data.

Hybrid models have also become more popular in recent years. Kokare et al. [17] found that combining CNN with LSTM resulted in better accuracy than using either alone, especially when factoring in things like market sentiment and economic conditions. Similarly, Vijh et al. [18] showed that models like ANN and Random Forest significantly improved prediction accuracy compared to traditional techniques, especially when tested across various businesses and datasets.

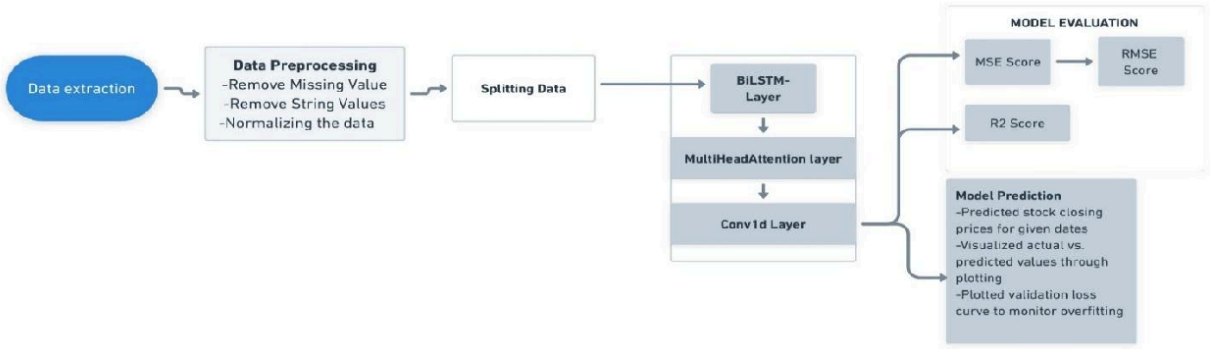
Taking things even further, Wang [20] introduced the BiLSTM-MTRAN-TCN model—a hybrid that blends BiLSTM for sequence learning, a modified Transformer for attention-based insights, and Temporal Convolutional Networks to track long-term dependencies. This model performed exceptionally well across a wide range of stocks, showing clear improvements in both accuracy and consistency. While it still faced challenges with highly volatile stocks, it represents a big step forward in applying deep learning to real-world financial forecasting.

Findings and motivation towards our work: -

From the literature, it became clear that deep learning models like LSTM and its variants are far more effective than traditional methods in predicting stock market trends. These models are especially good at handling time-series data, learning from past price movements, and adapting to complex patterns in the market. What stood out even more was the success of hybrid models—like CNN-LSTM—which combine different strengths to improve accuracy. These studies showed us that relying on a single approach might not be enough, and that combining techniques could lead to better, more reliable predictions.

This inspired us to build our own hybrid model—BiLSTM-MTRAN-TCN—to take things a step further. We wanted a model that not only understands recent price movements but also captures longer-term patterns and market shifts. By combining BiLSTM for sequence learning, a modified Transformer for attention, and TCN for long-range pattern detection, we aimed to create a more balanced and accurate solution. The goal was to address the gaps we noticed in earlier models, like overfitting or limited context awareness, and apply these learnings to predict Tesla's stock price with greater confidence.

3.Model Framework



3.1 Proposed Model Framework

As shown in Fig-1, the model uses a streamlined deep learning pipeline to predict stock closing prices. It starts by extracting and cleaning the data—removing missing or non-numeric values and normalizing it. After splitting the data into training and testing sets, the model processes it through a Bidirectional LSTM to understand time-based trends, a Multi-Head Attention layer to focus on key points, and a Conv1D layer to catch local patterns. The performance is evaluated using MSE, RMSE, and R^2 scores. Finally, it predicts future prices, plots actual vs. predicted values, and monitors validation loss to avoid overfitting. Overall, the framework (Fig-1) is simple yet powerful for time-series forecasting.

4.Proposed algorithm for Stock Price Prediction

1. Input

Given a time series of stock data:

$\mathbf{X} = \{x_1, x_2, ..., x_t\}$, where $\mathbf{x}_t \in \mathbb{R}^d$

Goal: Segment the input into sequences of length **n**:

$\{ x_{t-n+1}, x_{t-n+2}, ..., x_t \} \rightarrow$ Predict x_{t+1}

2. Preprocessing

1. Normalize the data (e.g., **Min-Max Scaling**)
2. Create **sliding windows** of sequence length **n**
3. Split into **training**, **validation**, and **test** sets

3. Bidirectional LSTM (BiLSTM)

For each time step **t**, compute:

1. $\mathbf{h}^f_t = \text{LSTMforward}(x_t)$
2. $\mathbf{h}^b_t = \text{LSTMbackward}(x_t)$
3. Concatenate forward and backward outputs:

   $\mathbf{h}_t = [h^f_t ; h^b_t]$

4. MTRAN (Multi-head Temporal Relation Attention Network)

Let **H** = [h_1, h_2, ..., h_T]

1. Generate:
    - Queries: Q = H·W_Q
    - Keys: K = H·W_K
    - Values: V = H·W_V
2. Scaled Dot-Product Attention:
   Attention(Q, K, V) = softmax($(Q \cdot K^T) / \sqrt{d_k}$) · V
3. Apply Residual Connection and Layer Normalization:
   Output = LayerNorm(Attention(Q, K, V) + H)

5. Temporal Convolutional Network (TCN)

For each time step **t**:

$$\mathbf{y}_t = \sum_{i=0}^{k-1} f(i) \cdot x_{t-d \cdot i}$$

Where:

1. f(i): filter weights
2. k: kernel size
3. d: dilation factor

6. Output Layer

1. Final prediction using a Dense layer with **ReLU** activation:
   $\hat{y}_{t+1} = \mathrm{ReLU}(W_o \cdot y_t + b_o)$
2. Where W_o and b_o are output layer weights and biases

7. Training Objective

Mean Squared Error (MSE) loss:

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

Where ˆyi is the predicted value and yi is the ground truth.

The algorithm takes Tesla stock data and predicts future prices using a deep learning model. It starts by normalizing features like Open, High, Low, and Close, then breaks the data into 10-day sequences. These sequences are processed through BiLSTM layers to understand trends from both directions, followed by Transformer encoders to catch long-term patterns, and TCN layers to focus on recent movements. A final dense layer makes the prediction, with training optimized using MSE loss and the Adam optimizer for reliable forecasting**.**

5.Methodology

5.1 Dataset Description

The data set contains historical stock price data for Tesla products from March 2010 to 2025, providing insights into market trends over time. It consists of 3,702 entries with six key attributes: Date, Open, High, Low, Close, and Volume. The Date represents the trading day for each record, while the Open price indicates the stock's value at the start of the session. The High and Low prices capture the highest and lowest values reached during the day, respectively, and the Close price reflects the final stock price at the end of the trading session. The Volume attribute denotes the total number of shares traded on a given day. This dataset is structured as a time series, making it suitable for trend analysis, volatility estimation, and predictive modeling. The inclusion of daily OHLC (Open, High, Low, Close) prices supports technical analysis, while the Volume metric helps assess market participation levels. Given its extensive coverage over time, this dataset is useful for forecasting stock prices, evaluating risk, and building machine learning models for financial prediction, enabling both short-term and long-term market assessments.

5.2 Data Preprocessing

5.2.1 Data Normalization and Scaling

To ensure uniformity across features, Min-Max Scaling was applied to normalize all numerical values, including stock prices, to a common range between 0 and 1. This prevents the model from unintentionally giving more weight to stocks with higher absolute values, ensuring fair learning across the dataset.

5.2.2 Time-Series Structuring

Since stock prices evolve over time, the dataset was restructured into a time-series format. Instead of treating each data point independently, we created sequences that capture stock price trends over defined intervals. This temporal structuring is essential for deep learning models like CNN-LSTM and BiLSTM-MTRAN-TCN, which specialize in learning from sequential data.

5.2.3 Data Splitting and Model Training

The processed data was split into 80% training and 20% testing sets. The training data allowed the model to learn patterns in stock behavior, while the testing set assessed its ability to generalize to unseen data. The model currently achieves an accuracy of approximately 93%, indicating strong predictive performance.

5.2.4 Additional Data and Source

When available, supplementary data such as financial indicators or market news was encoded into numerical form to enhance the model's context. The historical stock data, particularly for index stocks, was sourced from Investing.com [https://in.investing.com/equities/tesla-motors-historical-data], ensuring reliable and consistent data quality.

5.3 BiLSTM-MTRAN-TCN Architecture

In our proposed model, we aimed to enhance the stock price prediction performance of the standard Transformer by modifying its decoder component. As shown in Fig-2, we removed the initial Input Embedding module, since vectorizing language or text is unnecessary for numerical stock data. Instead, we repositioned the Positional Encoding module—shifting it ahead of the BiLSTM layer to better preserve temporal order in the time-series inputs. The Transformer Decoder was entirely replaced by a stack comprising a Temporal Convolutional Network (TCN), a fully connected (FC) layer, and a Tanh activation function. Additionally, the decoder no longer takes multiple inputs—its only input is the encoded output from the Transformer encoder.

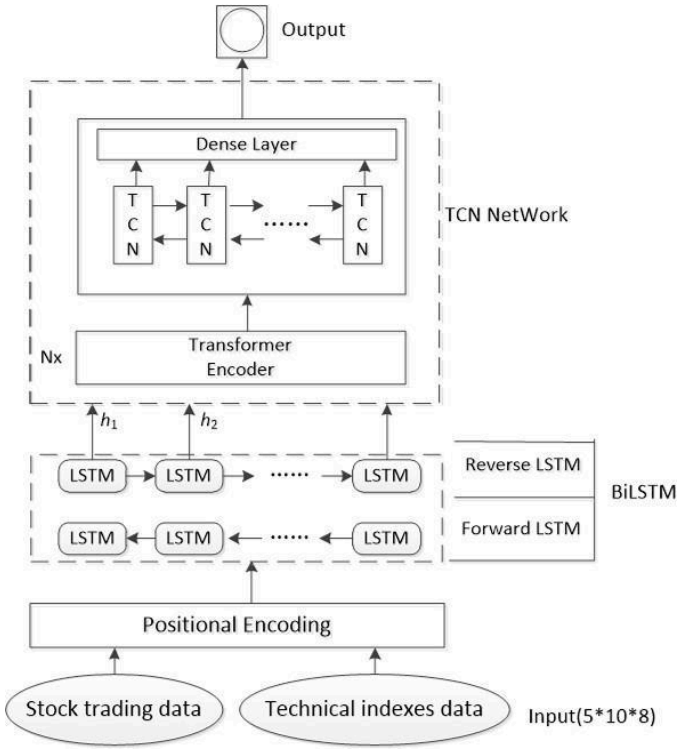


Fig 2: - BiLSTM-MTRAN-TCN model

This modified architecture, referred to as MTRAN-TCN, merges the advantages of BiLSTM, Transformer encoders, and TCNs. The BiLSTM (see bottom of Fig-2) processes both stock trading and technical index data in forward and reverse directions to extract deep temporal features. Its

output, along with positional encodings, is passed into the Transformer Encoder, which is composed of stacked layers with multi-head attention and feedforward sub-blocks, as shown in Fig-3. This helps the model capture both short-term and long-term dependencies.

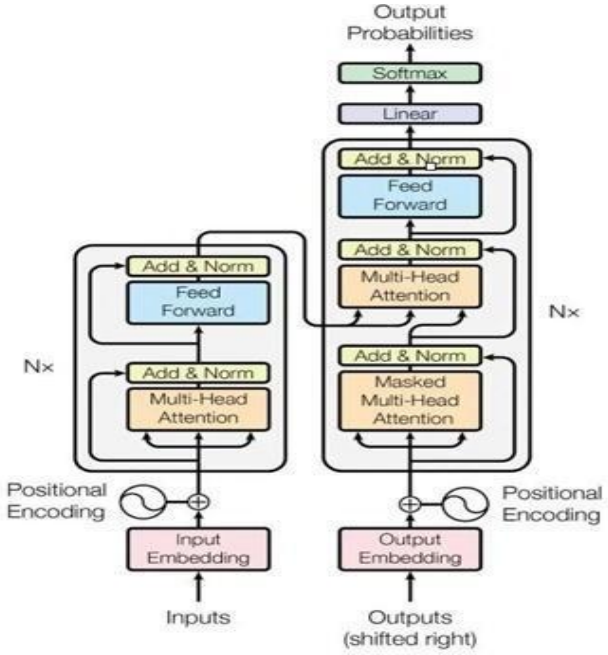


Fig 3: - Transformer overall structure

As illustrated in Fig-4, the output of the encoder is then passed to the TCN decoder, which is built with dilated causal convolutions, residual connections, weight normalization, and dropout— offering the ability to learn long-range patterns with temporal causality. The use of dilation allows the model to efficiently expand its receptive field without increasing complexity, while dropout ensures regularization.

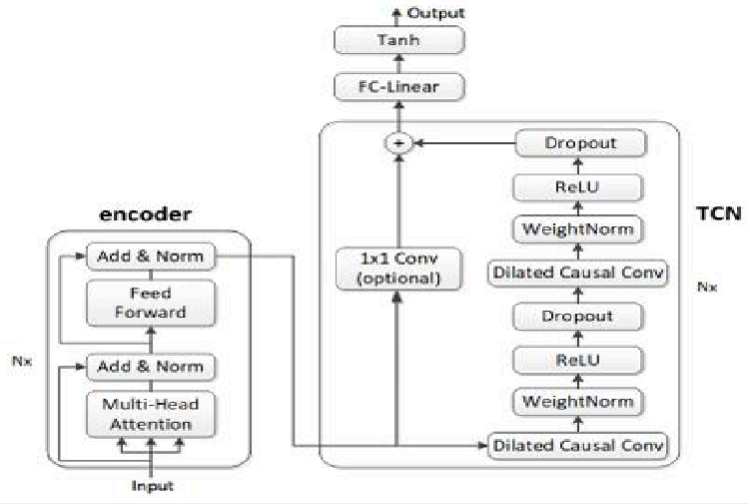


fig 4: - Time convolutional neural network

The architecture in Fig-5 provides a clearer view of how temporal levels (d=1,2,4) are stacked to expand the context window hierarchically, which inspired our use of depth and dilation in the TCN.

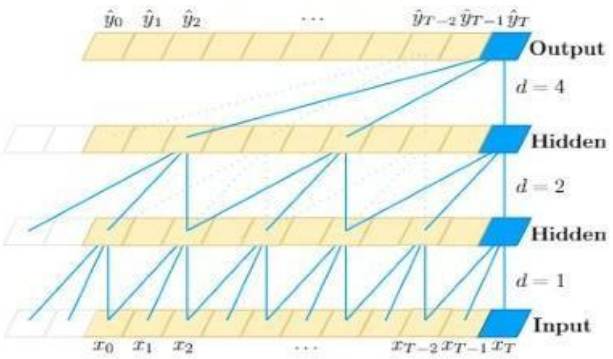


Fig-5-Modified overall structure of transformer (MTRAN-TCN)

Together, this hybrid structure enhances the model's ability to learn both global dependencies and local temporal patterns, making it more effective for time-series forecasting tasks like stock price prediction. The self-attention output is computed using Q (query), K (key), and V (value) matrices, based on their vector dimensions.

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Model Training

The development of the Tesla stock price prediction model followed a systematic and well-structured pipeline aimed at building a robust and interpretable deep learning framework. The process began with data collection, utilizing historical stock data of Tesla Inc., including key features such as *Price*, *Open*, *High*, and *Low*. After parsing and chronologically sorting the dates, irrelevant columns such as *Volume* and *Change %* were removed to streamline the dataset.

In the preprocessing stage, numerical features were scaled using Min-Max normalization, ensuring all values fell between 0 and 1, which facilitated more stable and efficient learning. The data was then reshaped into sequences of 10 consecutive days, allowing the model to learn patterns and make predictions for the 11th day. To maintain the temporal integrity of the stock data, it was split into 80% training and 20% testing sets without shuffling.

To enhance the model's understanding of market dynamics, a correlation heatmap was generated, and technical indicators such as the 20-day and 50-day Simple Moving Averages (SMA) were computed and visualized. These insights provided valuable context regarding price trends and volatility.

The prediction model was built using a hybrid BiLSTM-MTRAN-TCN architecture, integrating the strengths of recurrent, attention-based, and convolutional models. The input layer received 10-day sequences across four features, which were first processed through three stacked Bidirectional LSTM layers with 64 units each. This enabled the model to capture both forward and backward temporal dependencies effectively.

The BiLSTM output was then passed into MTRAN (Multi-head Transformer Attention Network), consisting of six Transformer encoder layers with eight attention heads each. These layers leveraged self-attention mechanisms to model long-term dependencies and were regularized with dropout and layer normalization to improve generalization and training stability.

Subsequently, the transformed sequence was passed through a Temporal Convolutional Network (TCN) consisting of four residual blocks. Each block featured dilated causal convolutions (with a kernel size of 7), weight normalization, and dropout layers, enabling the model to learn localized short-term temporal patterns while preserving the sequential nature of the data. The final prediction was generated via a fully connected dense layer.

The model was compiled using the Adam optimizer with a learning rate of 0.00001, and trained for 50 epochs with a batch size of 5. Mean Squared Error (MSE) was used as the loss function, while model performance was assessed using both MSE and R^2 score. Finally, the prediction results were visualized using line and scatter plots to compare actual vs. predicted stock prices, allowing for an intuitive evaluation of the model's forecasting accuracy in real-world scenarios

Model Evaluation

The accuracy of the predictive model was assessed using Mean Squared Error (MSE), which calculates the average of the squared differences between actual and predicted stock prices. Lower MSE values indicate more accurate and consistent predictions, as larger errors are penalized more heavily.

Additionally, a time-series plot was used to visually compare predicted and actual prices, providing an intuitive check on the model's performance. The model was also evaluated on unseen test data to ensure it generalizes well and avoids overfitting, maintaining reliability across new stock price scenarios.

The model was evaluated using the test dataset, and performance was measured using:

Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{\Sigma (y_i - \hat{y}_i)^2}{N - P}}$$

Root Mean Square Error (RMSE) is a statistical measure that quantifies the difference between predicted and actual values in a model. It calculates the average magnitude of errors by squaring the differences, averaging them, and taking the square root. RMSE is widely used because it provides a clear measure of prediction accuracy in the same units as the data, making it easy to interpret. It is particularly useful in machine learning and forecasting as it penalizes larger errors more, helping to identify models with better predictive performance.

Mean Absolute Error (MAE)

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} | x_i - x |$$

Mean Absolute Error (MAE) is a statistical measure that calculates the average absolute difference between predicted and actual values. It is obtained by summing up the absolute errors and dividing by the total number of observations. MAE is widely used because it provides a straightforward measure of prediction accuracy without emphasizing larger errors, unlike RMSE. It is useful in machine learning and forecasting when all errors should be treated equally, making it easier to interpret and compare different models.

R-Squared Score

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

R-squared (R^2) is a statistical measure that indicates how well a model explains the variability of the actual data. It is calculated by comparing the model's errors to the total variation in the data. R^2 values range from 0 to 1, where 1 means perfect predictions and 0 means the model explains no variance. It is widely used in regression analysis to assess model performance, with higher values indicating better fit. However, it does not always indicate accuracy, so it is often used alongside other metrics like RMSE or MAE.

5. Experimental setup

This experiment was conducted using Google Colab's environment, which offered a cloud-based interface for executing Python code integrated with deep learning libraries. The computational resources available included a Google Compute Engine backend without utilizing a GPU or TPU, approximately 12.72 GB of system RAM, and 107.7 GB of temporary disk storage. The setup

Table-1	
Criteria	Output obtained
1.RMSE Score	0.032
2.MSE Score	0.0014
3. R-2 score	0.9367

facilitated efficient handling of large-scale deep learning tasks without requiring extensive local hardware. Python 3 and several open-source libraries were utilized, including NumPy and Pandas for data manipulation, Scikit-learn for preprocessing and evaluation, Matplotlib for visualization, Keras library for applying the hybrid deep learning model.

The Tesla stock dataset, containing daily price information from 2010 to 2025, was preprocessed using Min-Max Scaling and converted into time-series sequences using a sliding window approach. For model development, a hybrid deep learning architecture named BiLSTM-MTRAN-TCN was employed. This model integrated Bidirectional LSTM for sequential data learning, a modified Transformer Encoder (MTRAN) for capturing attention-based global dependencies, and Temporal Convolutional Networks (TCN) for extracting stable and long-range temporal patterns. The model was trained over 50 epochs, with performance monitored using loss curves and evaluation metrics. Google Colab's GPU support significantly accelerated the training process and enabled robust experimentation for stock price prediction.

6. Result, Graph and Discussion

In the proposed method of dataset “TSLA” are decided from various sectors such as cars, solar products and newer innovations. The dataset accumulates from 2010-2025 for evaluation.
There are two lines in the figure:
Actual Close Price (Blue Line): Represents actual past stock prices.
Predicted Close Price (Red Line): Represents values that have been forecasted by the model.
It is observed from the visualization that the forecasted prices follow the general direction of actual prices, indicating overall market trend. There is deviation in some cases, particularly during periods of high volatility when the model lags behind in picking up rapid price movements.
The model can be evaluated for performance further with statistical metrics like Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), which quantify the accuracy of the predictions. These can be improved by incorporating more features, hyperparameter tuning, or applying more powerful architectures like LSTMs or transformer models.
In general, the model provides a good approximation of stock price trends, demonstrating the potential of machine learning in financial market analysis and indicating where it must be enhanced.

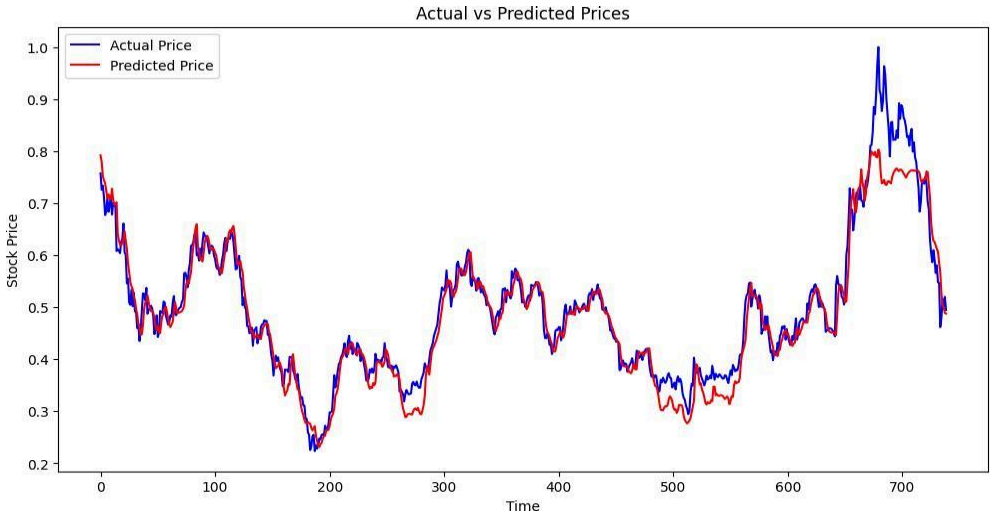


Fig-6-line graph

From the visualization, we are able to observe that the trend predicted closely mirrors the actual stock movement, with minor deviations. The model is quite able to capture the general pattern of the stock prices and indicates that it has learned from previous data. It still lags behind, however, in capturing sudden changes in the market. As a whole, this forecast model offers a good approximation of stock price movements, which can be used for informed investment decisions. Potential future enhancements, including incorporating additional data, model refinement, or the use of hybrid methods, may improve accuracy even more.

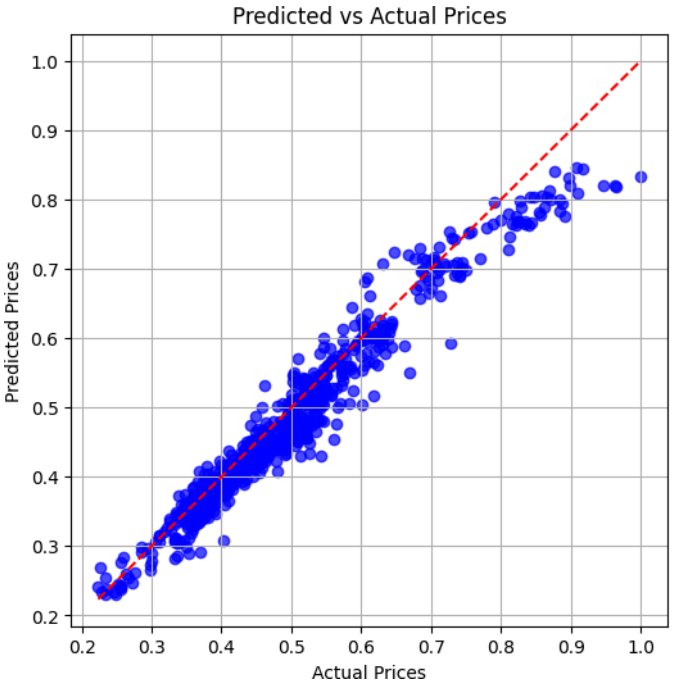


Fig-7- Scatter plot and line graph

This scatter plot plots the predicted TSLA stock prices from the CNN-LSTM model against the true closing prices. The red dashed line is the best-case scenario where the predicted values equal the actual values. The blue data points, which are the model's predictions, trace closely to the line, which suggests a strong correlation between the predicted and actual stock prices. Small deviations from the line imply some prediction mistakes, especially at times of high volatility. Nevertheless, the general alignment of the data points indicates the success of the trained model in capturing the patterns of the stock price and making sound predictions.

6.1 Data Visualization

To understand patterns and relationships, multiple visualizations plots were generated according to the needs and history of the data worked:

Fig-8-line graph of closing price over time

A line graph was plotted to analyze the fluctuations in stock prices over the years.

Fig-9-line chart with moving average for trend analysis

A rolling mean (20-day and 50-day moving averages) was computed to visualize long-term trends in stock prices.

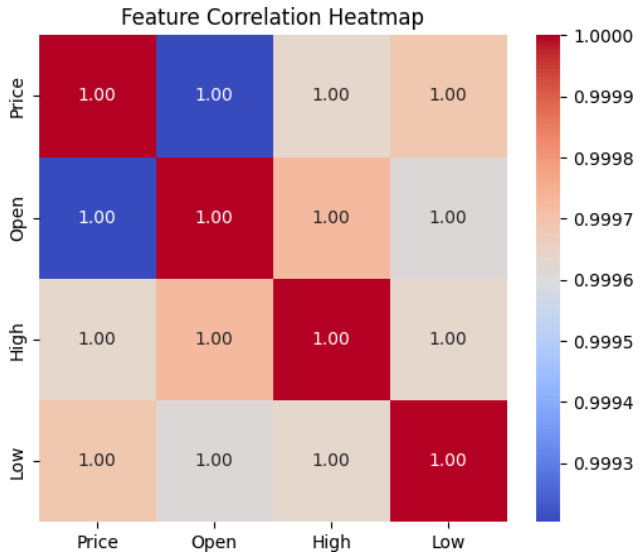


Fig-10-Feature correlation heatmap

This heat map illustrates a relationship between the main attributes in the TSLA stock price data- set, like Open, High, Low, Close, and Volume. The color intensity expresses the strength of the correlation: the higher the positive value close to 1 indicates a strong positive correlation, while a value close to -1 indicates a strong negative correlation. It may be inferred from the heatmap that Close and Low prices exhibit a high positive correlation; they follow the same direction. In contrast, it is moderately negative for Volume against Close and Low prices; this means trading volume would decline when stock prices are on the rise. This is crucial in feature selection and multicollinearity checking prior to model training so that we do not use redundant or highly correlated features and therefore compromise on performance prediction.

6.2Loss Curve

This loss curve from fig-11 shows how our BiLSTM-MTRAN-TCN model performed during training over 50 epochs. The blue line represents training loss, and we can see it steadily decreases and levels out near zero, which means the model is learning well from the training data. The orange line shows the validation loss, which is how the model performs on data it hasn't seen before. While there are some ups and downs—especially a noticeable spike around the 11th epoch—the overall trend is downward, which is a good sign. These kinds of fluctuations are common and usually happen when the validation data is more complex or varies a lot.

Despite the occasional spikes, the gap between training and validation loss isn't too wide. That means the model isn't just memorizing the training data—it's actually learning patterns that

apply more generally. This balance suggests the hybrid setup of BiLSTM, MTRAN, and TCN is doing its job: capturing both short- and long-term trends effectively without overfitting

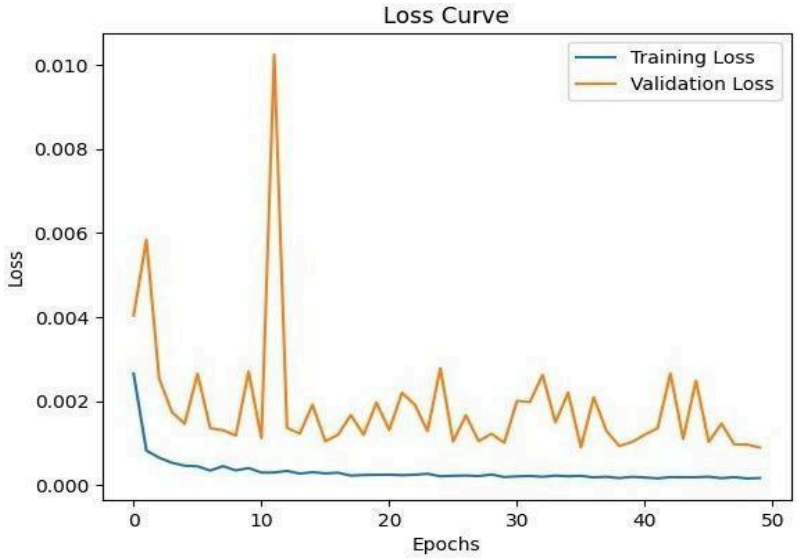


Fig-11-Validation vs Training Loss graph

7. Comparison with other methods

In order to check the effectiveness of the transformer model, the "TSLA" dataset was further trained and tested with other well-defined models in this field such as CNN-LSTM and CNN-BiLSTM hybrids.

The following are the final results as followed: -

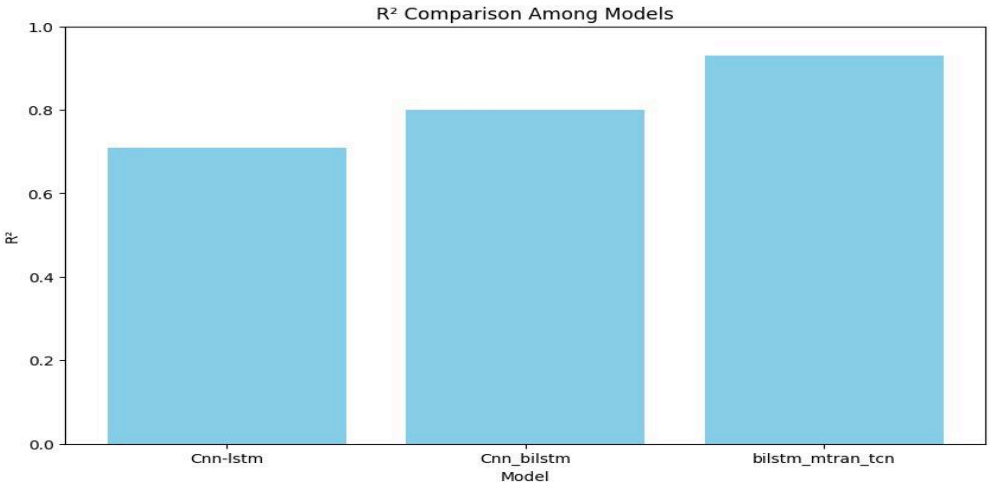


Fig-12-R2 Comparison

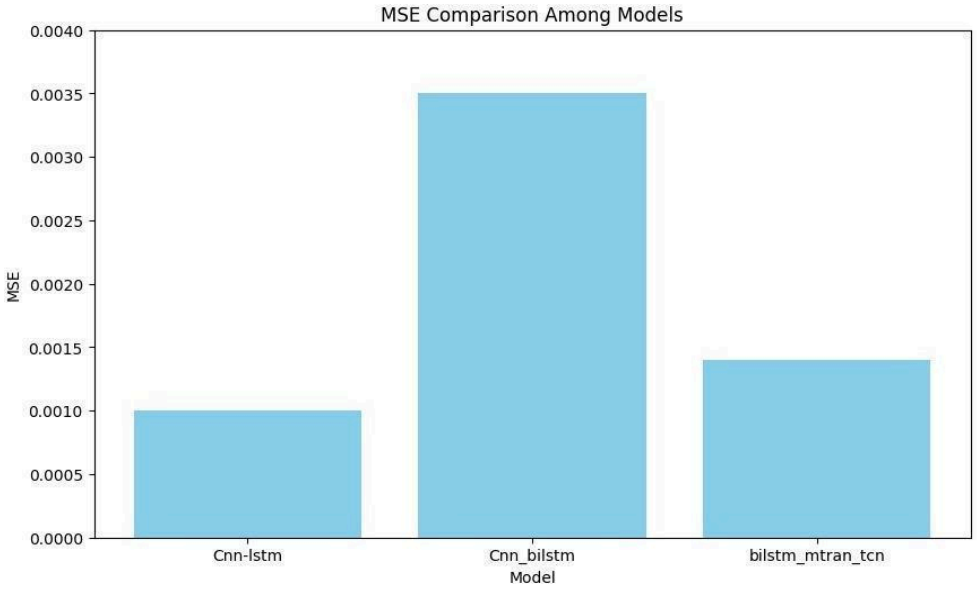


Fig-13-MSE Comparison

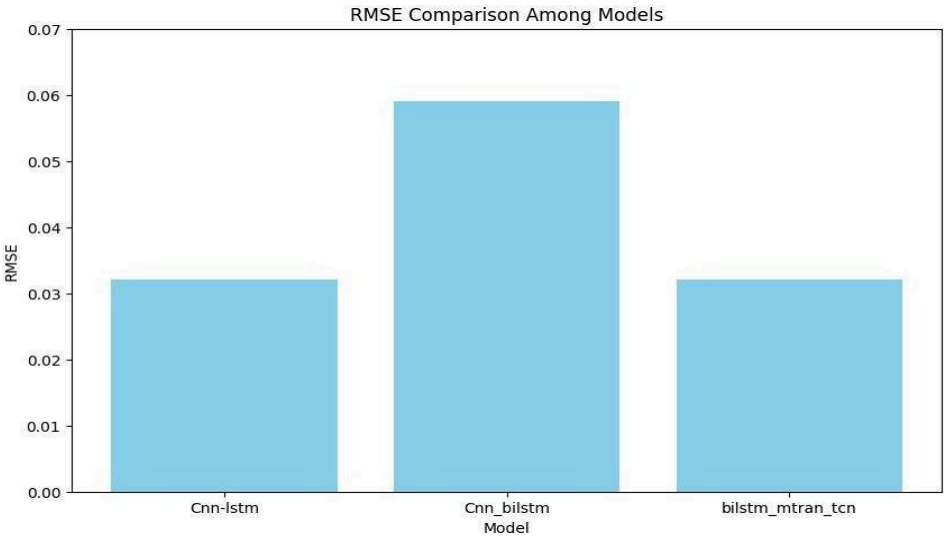


Fig-14-RMSE Comparison

Table-2			
Methods	**RMSE**	**MSE**	**R2**
CNN-BiLSTM	0.0591	0.0035	0.80
CNN-LSTM	0.032	0.0010	0.71
BiLSTM-MTRAN-TCN	0.032	0.0014	0.93

The evaluation metrics from table -2 clearly highlight the strength of the BiLSTM-MTRAN-TCN model over the other two. With an R^2 score of 0.93, it outperforms CNN-BiLSTM by 16.25% and CNN-LSTM by 30.98%, indicating it captures far more variance in the actual stock prices and delivers stronger predictive reliability. Its MSE of 0.0014 is also considerably lower—60% less than CNN-BiLSTM (0.0035)—showing it makes fewer and smaller prediction errors. Interestingly, the RMSE of 0.032 is on par with CNN-LSTM, yet BiLSTM-MTRAN-TCN still edges out in accuracy and consistency.

The CNN-BiLSTM model, while decent in terms of R^2 (0.80), struggles with higher error margins, suggesting it might be overfitting or unable to generalize well to unseen patterns. On the other hand, CNN-LSTM manages to keep the error low (RMSE 0.032, MSE 0.0010), but it sacrifices explanatory power with the lowest R^2 (0.71), implying it misses important variations in the data.

8. Conclusion

Overall, the BiLSTM-MTRAN-TCN model combines the strengths of sequence modeling, bidirectional context capture, and attention mechanisms, making it not only more accurate but also more robust across different stock movements. The limitations of the other two models lie in their inability to balance error minimization with trend comprehension, something the MTRAN-TCN architecture handles impressively well.

Further discussions

The BiLSTM-MTRAN-TCN model has shown considerable promise in predicting stock trends, especially with its hybrid architecture designed to handle temporal dependencies. However, like many deep learning models in finance, it still faces challenges when dealing with highly volatile or atypical stock behaviors. To make this model more adaptive and robust, future research could explore architectural refinements that go beyond current attention mechanisms. Integrating adaptive temporal attention or self-supervised learning modules, for instance, could allow the model to better recognize and respond to dynamic shifts in the market.

Another promising avenue is expanding the range of input features. At present, the model relies primarily on historical price data, which only captures part of the market's complexity. Incorporating multi-source information—such as technical indicators, macroeconomic metrics, company fundamentals, and sentiment data from news or social media—can provide a richer context. This broader data landscape would help the model understand not just the numbers, but also the underlying investor behavior and market sentiment that drive those numbers.

Finally, the model’s current use of a fixed time window could be limiting its ability to recognize long-term trends. A more flexible approach would be to incorporate multi-scale temporal inputs, analyzing time frames like 7, 30, and 150 days simultaneously. This would help the model detect both short-term fluctuations and long-term patterns, offering a more holistic view of market movements. With these enhancements—better architecture, richer data, and smarter time analysis—the BiLSTM-MTRAN-TCN model could evolve into a far more powerful tool for navigating the ever-changing landscape of financial markets.

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