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# A Hybrid LSTM–Attention Framework for Multivariate Stock Forecasting with Macroeconomic Indicators

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Abstract

There are numerous factors that can influence the prices of the stock, such as the company-specific indicators of performance and macroeconomic factors. Furthermore, such a combination of interdependent and intricate financial and economic variables makes it intrinsically hard to predict such price movements. In order to manage this complexity, the current research incorporates the data of the stock market, as well as the principal macroeconomic indicators, into a single prediction model.

It is proposed to use a hybrid model based on LSTM and Attention, whereby the LSTM element models the time-related factors in a periodic data set, and the Attention element distinguishes and highlights the most significant factors in the share market prices. This combination approach will allow the model to identify the timing of changes in the market as well as the foregoing effects that are less significant. Empirical evidence shows good explanatory strength, where the R 2 value is about 0.97 and a low level of error of prediction. Quadruplication. The backtesting also shows that the model has a good payoff on investment, and it continues to outperform the traditional forecasting methods.

All in all, the hybrid LSTM-Attention model will make stock market prediction more reliable and practically applicable. The model helps to make more informed and data-driven decisions on portfolio management and the critical drivers of the market.

**Keywords:** Financial time series forecasting, Deep learning models, Temporal data analysis, Feature attention mechanisms, Economic trend prediction, Investment decision support

## I. Introduction

The use of machine learning has been the subject of decades of academic and industrial attention. Although it has begun well, the development of this area was even slower in the second half of the twentieth century, in large part, because of the extremely expensive nature of computational resources and of large, structured datasets. Machine learning systems require a significant amount of data and processing power to extract useful patterns of data, neither of which was widely available at the time, except to well-funded institutions. This was changed by the next revolution in the computer industry, which brought down considerably the cost of computation and made possible the production of large amounts of digital data, storage, and its accessibility in large volumes. All these developments led to accelerated changes in machine learning studies and usage.

The technological change has also influenced the development of stock market activities. Before the digital era, trading of stocks was based on paper processes, and the buyers and sellers had to be present in the trading rooms, and the ownership had to be in the form of paper certificates. A paradigm of shifting to the Dematerialization (DEMAT) system was introduced, with the substitution of paper certificates with computer-based records. In this system, the stock dealings are carried out via the use of electronic transfer as well as the digital registration, which significantly enhances efficiency, transparency, and availability of financial markets [1].

Proper forecasting of the stock market has brought about great significance in investment decisions, investment portfolio optimization, and long-term financial planning. Nevertheless, it remains a complex task, a nonlinear behavior, there is a high volatility; moreover, there is a strong interdependence between financial and macroeconomic variables that makes prediction rather difficult [2]. The traditional methods of forecasting, used in many cases, are based on univariate or single-source data and are insufficient to reflect the complex nature of the contemporary financial market. Moreover, unpredictable economic, political, or geopolitical occurrences bring in more uncertainty and limit the predictability of classic models even more [3].

The challenge of deep learning hybrid approaches has recently attracted attention to their efficiency in combating these challenges. Long Short-Term Memory (LSTM) networks are uniquely suitable for time series models, as they are capable of both considering long-term time series effects, as it offers long term dependencies, in addition to attention mechanisms, which enhance interpretability by attaching more weight to the most effective input features [4]. In the Indian financial scenario, both the use of algorithmic trading options and multivariate modeling systems have been proven to have significant potential in terms of improving performance in portfolios, as well as in trade execution. The state-of-the-art architectures, incorporating convolutional neural networks (CNNs), LSTMs, and attention layers, have also enhanced the accuracy in forecasting with a joint learning of both time and structural patterns in financial data [5].

Although all these steps have been made, most of the existing forecasting models do not incorporate or use macroeconomic variables, or those that do so in a restricted form, and they do not fully capture the macroeconomic variables in a holistic multivariate model [6]. In order to overcome this constraint, the current paper suggests a Hybrid LSTM -Attention Framework: a bivariate model should combine data on stock prices and macroeconomic factors. By addressing the long-term temporal trend, focusing on major market attributes, and providing statistically prioritized forecasts, the proposed approach creates an improved forecasting performance and interpretation of the results. In addition to providing a methodological contribution to the literature on financial forecasting, the model provides a viable decision support instrument to investors and portfolio managers and makes it easier to develop data-driven strategies to reduce risk and maximize returns in dynamic markets.

## II. Methods

### Research Design

The research design used is the quantitative experimental research design to construct and test a Hybrid LSTM-Attention deep-learning model in predicting stock prices. The proposed model has a multivariate structure in that it combines the past stock price with technical and macroeconomic data, which allows it to not only represent intricate dependence over time, but also the relative importance of major driving forces of the markets.

### Datasets

Yahoo Finance has been selected as the source of historical stock price data of HDFC Ltd., and the open, high, low, and close (OHLC) prices, together with the traded volume, were obtained. On the basis of this information, all popular technical indicators, including Relative Strength Index, Moving Average Convergence Divergence, and Exponential Moving Average, were calculated with the help of the TA-Lib and pandas-ta packages. Moreover, macroeconomic variables (interest rates and inflation rates) were also obtained through the authoritative national sources, i.e., the Reserve Bank of India (RBI) and the Ministry of Statistics and Programme Implementation (MOSPI). All sources of data have been in a systematic manner documented in order to maintain transparency, reproducibility, and integrity of data.

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Experimental Procedure

The workflow in the experiment was organized systematically. To begin with, historical data in the stock market as well as economic statistics, were averred and time-adjusted in order to make data sets consistent. After this, feature engineering was carried out through the calculation of technical indicators and bringing all the variables into synchronized multivariate time-series sequences. The processes involved in the data preprocessing step consisted of dealing with missing values, scaling of features, and generation of supervised learning sequences with the help of the sliding window method.

This was followed by the creation of the Hybrid LSTM -Attention model with the help of TensorFlow/Keras, which is explicitly programmed to take in the inputs as multivariate time-series, as well as highlight the key features in the flashlight of attention. A set was further split into training, validation, and test blocks with no dispensation of the chronology in order to eliminate look-ahead bias. Direct values were optimized to model the best hyperparameters. Lastly, standard performance measures such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R 2) were used to test the predictive power of the model.

Software and Analytical Tools

The Python programming language (version 3.x) was used to analyze it. Pandas and NumPy were used to process data and to make numerical calculations, whereas TA-Lib and pandas-ta were employed to make technical indicators. TensorFlow/Keras (augmented by Scikit-learn to do preprocessing and evaluation tasks) was used in model development and training. Matplotlib, Seaborn, and Plotly were engaged to perform data visualization as a tool to support the exploratory analysis and interpretation of the obtained results. Comparative evaluation. Baseline statistical models were constructed with the help of Statsmodels. The general development setting comprised Jupyter Notebook alongside Google Colab, and data were retrieved by the API used in the Yahoo Finance, as well as the official sites of RBI and MOSPI.

III. Results

The standard error and goodness-of-fit measures were used to assess the performance of the proposed Hybrid LSTM Attention model. The value of the Root Mean Squared Error (RMSE) was obtained to be 15.09, so the average value of the error between the predicted and actual stock prices is estimated to be 15 units. The fact that RMSE has higher penalties on larger errors indicates that this model has a reasonable control over the material deviations in prediction.

After this, Mean Absolute Error (MAE) was obtained as 11.89, which is the mean difference between the predicted and observed values (in absolute form). Since MAE gives equal importance to all the errors and is not sensitive to extreme values, it gives a consistent and understandable value of the overall average predictive accuracy of a model. Large errors of prediction are not frequent since the MAE is relatively low in contrast with the RMSE.

The value of the coefficient of determination (R 2 ) was 0.9673, and this indicates that close to 96.73% of the variation in actual stock prices is accounted for by the model. The large value of R 2 indicates that the model is highly predictive of the observed and predicted prices and receptive to learning complex trends using multivariate financial and macroeconomic data.

The fact that the RMSE and MAE values suggest that the prediction error is not zero, but on the other hand, the very high value of R 2 shows that the model has high potential to generalize. This is especially noteworthy in the case of time-series forecasting, where any inaccuracies in the performance can increase with time, highlighting the strength and practicality of the suggested method.

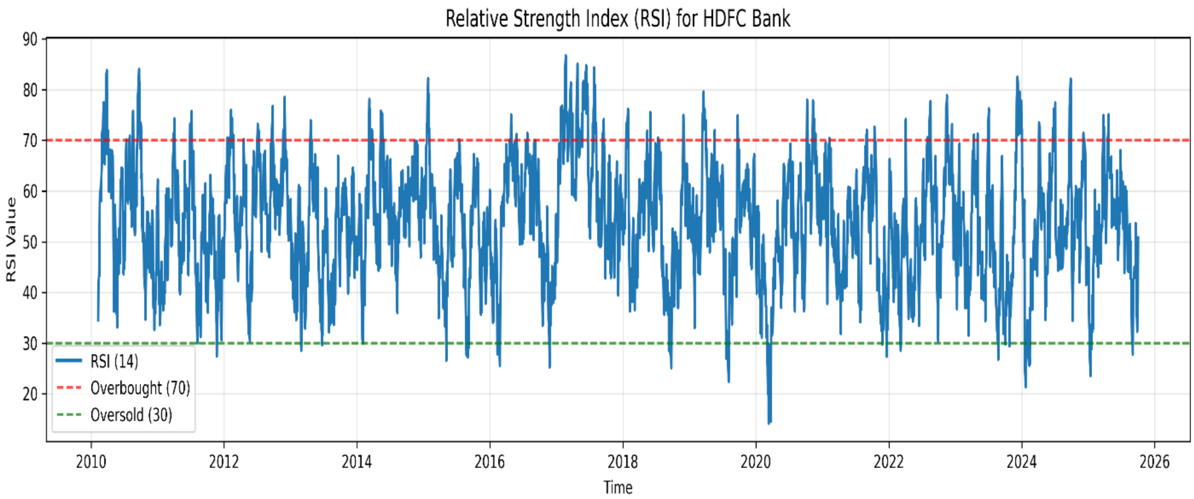


Fig. 1 RSI of HDFC Bank

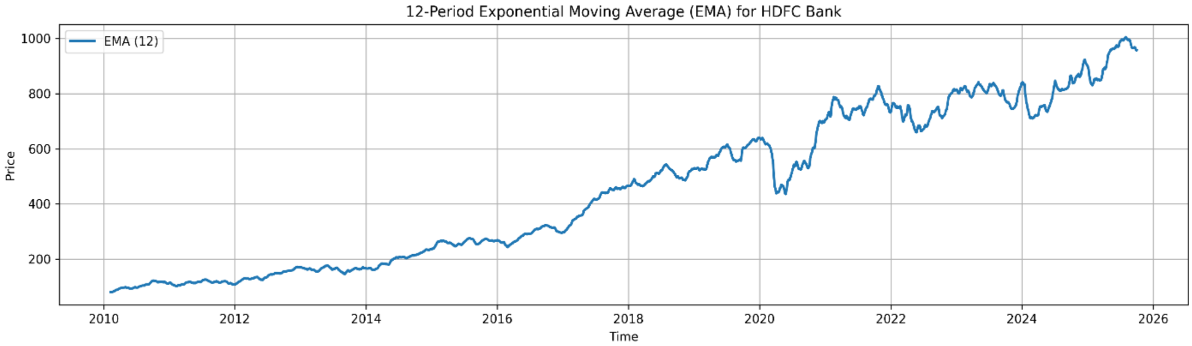


Fig. 2 12-Period EMA of HDFC Bank

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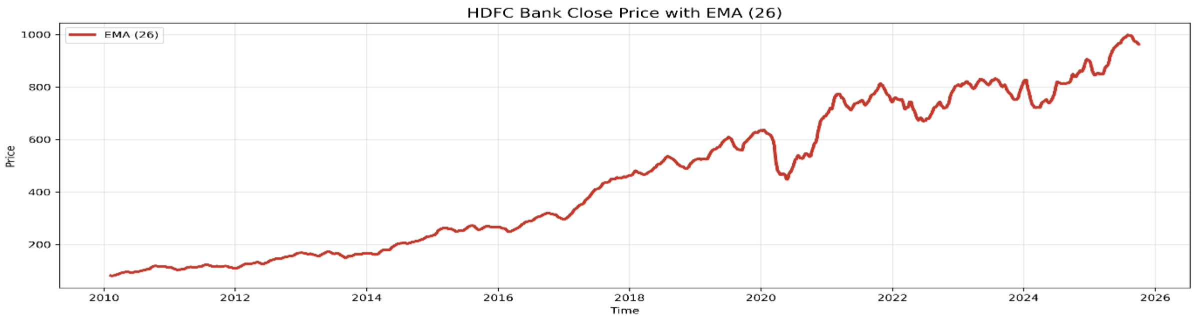
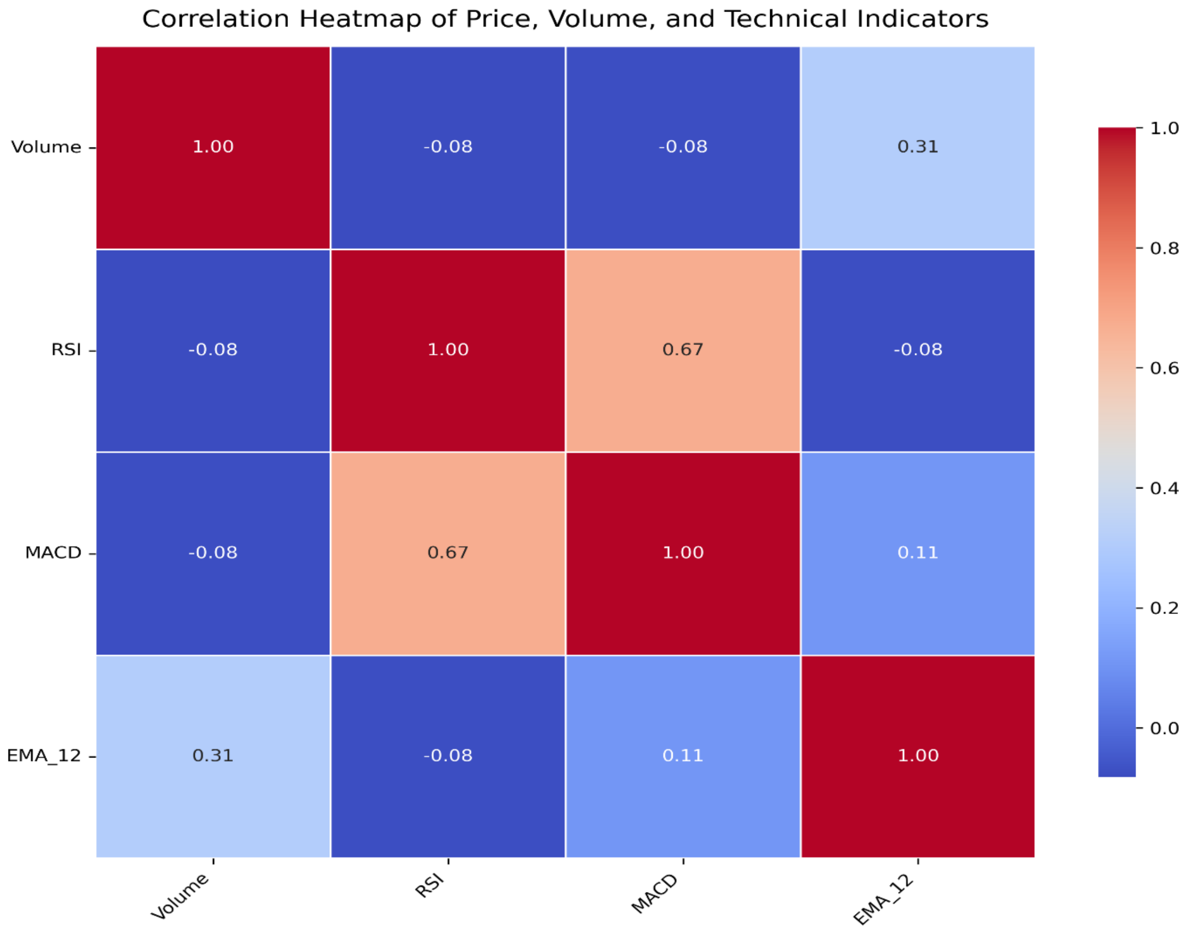



Fig. 3 26-Period EMA of HDFC Bank

Fig. 4




Correlation Heatmap of HDFC Bank

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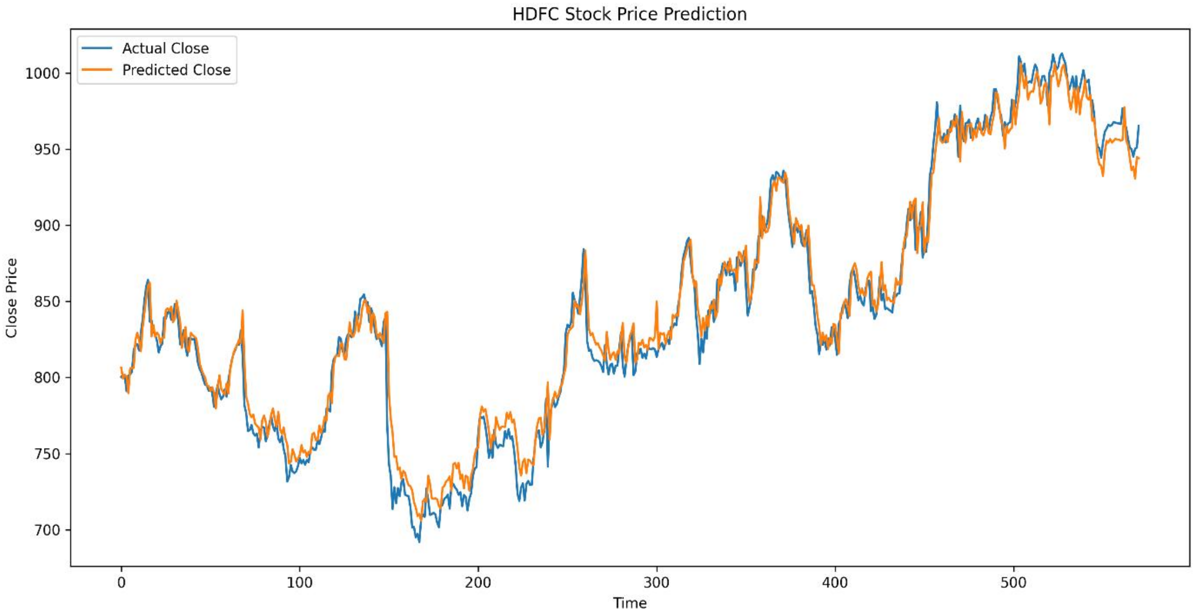


Fig. 5 Comparison of Actual and LSTM-Predicted Closing Prices for HDFC Bank

**Model Performance**

| **Metric** | **Value** | **Interpretation** |
|---|---|---|
| Root Mean Squared Error (RMSE) | 15.09 | Average prediction error magnitude. Larger errors are penalized more. |
| Mean Absolute Error (MAE) | 11.89 | Average size of prediction errors. Treats all errors equally. |
| $R^2$ Score (Coefficient of Determination) | 0.9673 | Indicates that ~96.73% of the variance in target values is explained by the model. |

Conclusion

The objective of the current study was to use deep learning to improve the predictability of stock prices by creating a hybrid framework that will incorporate variables in the market with the macroeconomic ones. Through harnessing the sequential learning power of Long Short-Term Memory (LSTM) networks and the feature-weighting capabilities of attention structure, the model not only succeeded in capturing complex-temporal relationships but also highlighted those determinants of price movement that had the strongest impact.

The empirical findings show that the proposed framework provides good predictive power, which is indicated by low values of RMSE and MAE and a high value of the coefficient of determination ($R^2$). The macroeconomic aspects of the model, including the usage of macroeconomic indicators, also added an informational layer to the model itself and led to its higher predictive ability in comparison with other methods that utilize historical price data only.

This study adds a valuable input to the financial forecasting literature via introducing an example of Multivariate LSTM Attention architecture that has practical implication to investors, traders, and portfolio managers who require data-driven decision support. However, some constraints are observed, which include relying on data quality, a higher complexity in computation, and a reduced reaction to uncommon or unexpected market shocks.

Further development of the framework in future studies can incorporate additional sources of data described as alternative data sources, like the financial news sentiment, social media signals, or economic indicators on a global level. Application to other fields of portfolio optimization, risk management, and real-time trading is also a potentially fruitful directions of creating more adaptive and intelligent financial forecasting models.

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