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Triple Attention-Based Hybrid Deep Learning Framework for Enhanced Stock Market Prediction

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Abstract: Stock price prediction is a complex problem because financial time series data are volatile and complicated. The model should learn the temporal relationship and complex spatial patterns in data for precise stock price prediction. Conventional methods used for stock price forecasting have many limitations regarding handling nonlinear, complex, and dynamic data. This study assesses a hybrid deep learning model integrated with a triple attention mechanism to predict stock prices. It is experimental that the proposed MTA-HDCRNN model performs well on intricate data. The deep CNN works well on finding the local patterns in the data, whereas the simple RNN supports to learn sequential data. The triple attention mechanism emphasizes which features to focus on and where to focus. The dataset used for analysis is the BSE and Nifty 50. Web scraping is done to get the news data. Feature extraction includes statistical features, entropy features, PCA features, and technical indicators. Overall, the complete architecture of the proposed model is vigorous. It is observed that there is a 2% to 6% decrease in error values when the model is compared with existing state-of-the-art models. Experimentation shows that the proposed model enhances the stock price prediction, making it useful for investors and financial analysts for decision-making.

Keywords: Financial Time Series, Stock Market, Deep Learning, Attention Mechanism

1. Introduction

Financial analysis of the stock market based on historical data, various parameters, and indicators is an essential aspect in predicting the stock market for better earnings. This has created a growing trend among the investors, researchers, and analysts to integrate computer skills, AI-based analysis, and knowledge of financial technologies towards more accurate prediction [1]. Various governing factors decide the future of market indices and hence their overall performance. To do more scientifically, there is a need to develop a model that will be based on historical data, a critical evaluation of various parameters. Analysing this data and decoding the various temporal dependencies and complex spatial patterns is key to accurate prediction of the stock market. The further challenge lies in identifying all the direct and indirect governing factors, establishing their interdependency, and decoding the complex relationship among all these parameters [2].

The financial assets like stocks, futures & option contracts, various indices in a monetary system decide the Financial Time Series. The stock market performance depends on a variety of factors, including business news, economic news, government policies, geopolitical situation, and natural or man-made disasters. The two main exchanges in India are NSE and BSE. The NSE has over 2000 listed entities, and the BSE has over 5000 listed companies. Almost all of India's largest trading companies are listed there. The fluctuation in the stock's price is due to the macroeconomic environment, industry development, business operations, and investments. The complex non-linear relationship between government policy, business policy, investors' mindset, political turmoil, and economic variables all influence stock prices, making stock market prediction a true challenge.

With a larger number of retail customers growing on the stock market, the stock market provided a platform for the inclusive financial growth of people and their well-being. Forecasting is a method for making predictions by examining what has already happened and what is happening now. Although forecasting is challenging, it is essential in many facets of life, such as business and industry, banking, economics, and medicine. In recent years, corporations and the general public have been more interested in stock market predictions. The financial sector's advancements are responsible for the economy's overall growth and stability. Forecasting is a somewhat challenging task in business, but it's crucial because it allows you to plan for the future. Making comfortable, pleasurable money is something we all desire to do to make life easier. Stock investing is a simpler method of asset growth. A person may occasionally lose their assets as a result of using the incorrect investment strategy policy. Errors and losses are also a result of manually predicting stock values.

Because of the intricate nature of the stock market, predicting stock market prices is one of the most challenging careers in financial forecasting. Numerous variables affect this, including the company's performance, governmental regulations, international political and economic conditions, etc. Investors seek to choose a strategy that can reduce stock market investing risk and swiftly ensure it. In an attempt to solve the problem, numerous researchers have put forth new approaches and techniques to predict the stock value in recent years more accurately.

For assessing stock market predictions, early researchers employed conventional techniques like GARCH, ARIMA, ARMA, and so on. The ARMA technique is used to do the basic time series stock analysis [3], but it is hampered by outside influences and does not produce reliable forecast outcomes. The ARIMA model's [4] prediction of stock price fluctuations offers useful concepts for time series stock prediction based on the GARCH model's time window approach. Because traditional stock returns are volatile, models become more complex, making it harder to capture relevant features and preventing the development of the intended forecast output.

Stock market value forecasting makes use of several machine learning techniques [5-7]. These techniques look for patterns, trends, and signals that could show an indication of future price movements. This is done by analysis of vast amounts of historical and current financial data. Deep learning methodologies [8] are extensively used in stock market forecasting. They can recognize complex, non-linear patterns and temporal connections within wide financial information. The deep learning models yield successive results through time series. These results are more precise and efficient than those obtained by traditional measures.

In recent years, hybrid methods have been developed. These methods are evolving as powerful techniques for tackling challenges faced by conventional methods. CNNs are skilled at extracting local traits from time series data. Thus, allowing them to recognize short-term patterns and variations in stock prices. RNN and LSTM models are good at exhibiting sequential dependencies over the course of time [9] [10].

However, even these advanced models struggle with assessing which traits are most influential when the data is quite erratic.

2. Related Work

The following section provides further insights into the evaluation of stock market prediction using various deep learning methods. Yu and Yan [11] proposed a PSR method integrated with an LSTM deep neural network. The model outperforms the traditional approaches. However, external factors such as the news or sentiments are not taken into consideration. Guangyu Mu, *et al.* [12] presented an optimised deep learning architecture. The Sparrow search optimization algorithm is used to integrate with LSTM and multi-source stock price data. By hyperparameter tuning and sentiment analysis, prediction effects have been enhanced. Huang *et al.* [13] proposed an ML-GAT method for forecasting stock market returns. It is equipped with capturing and updating features to build understandability and consistency, notwithstanding financial risk. Muhammad Khan *et al*. [14] presented the EMD-LSTM model. The EMD generates highly correlated elements. These elements are thereafter exploited to build the LSTM network. The model enhanced performance efficiently, but lacked prediction accuracy. Somenath Mukherjee *et al.* [15] proposed an ANN-CNN method. However, it faced overfitting and computational complexity issues. This limitation affected the inference time and accuracy of stock prediction.

For better time series forecasting, deep learning models have recently added the attention method [16]. Attention mechanisms assist models in focusing on the most relevant data by dynamically assigning weights to input attributes or time steps. A study shows that researchers have combined attention-based techniques with deep learning models to improve predictive performance by emphasizing critical patterns in financial data. Chen et al. developed a dual-attention-based stock price trend prediction model, combining piecewise linear regression and convolutional neural networks to extract long-term and short-term market features, demonstrating superior prediction accuracy on stock indexes [17]. Zhang et al. developed an attention-based LSTM model for financial time series prediction, enhancing feature selection, reducing dependency, and improving interpretability, demonstrating superior accuracy on three financial datasets [18]. Lee *et al.* developed an attention-based BiLSTM model for stock trading strategy design. Here, 68.83% was the prediction accuracy. The model enhances prediction accuracy along with better ROI [19]. Abbasimehr and Paki [20] used the concept of multihead attention integrated with an LSTM model. Here, the attention mechanism highlights vital time points, and LSTM captures the long-term dependency in the data.

Table 1. Attention Models

References	Methodology Used	Dataset of stock index	Features Used		
			Historical data	Media News	Technical Indicator
[17]	Dual Attention + PLR + CNN	China: CSI 300, SSE 50, and CSI 500	✓	×	✓
[18]	LSTM + Attention	Nasdaq: American AT&T company	✓	×	×
[19]	BiLSTEM +Attention	Taiwan: TPE0050	✓	×	✓
[20]	LSTM+ Multihead attention	16 public time series	✓	×	×
[21]	CNN+LSTM+ spatial-temporal attention (STACN)	DJIA	✓	✓	×
[22]	CNN+ BiLSTM+ Attention-based model	China: CSI 300 Index	✓	×	×
[23]	MKG + Dual Attention Networks (DANSMP)	China: CSI	✓	✓	×

The model is experimented on 16 public datasets and outperforms ARIMA, ETS, and other hybrid models.

Lin et al. proposed an STACN model [21] concentrating on a spatial-temporal attention-based convolutional network. In experimental results, the model achieves a superior precision over CNN and LSTM. Zhang et al. developed a CNN-BiLSTM-Attention model for stock price forecasting, demonstrating superior accuracy compared to other models tested on twelve stock indices [22]. Zhao et al. developed a hybrid relational market knowledge graph and Dual Attention Network for improved stock momentum spillover prediction, demonstrating superior performance on the CSI100E and CSI300E datasets [23]. Table 1 shows the summary of attention models. It encompasses spatial-temporal attention, multi-head attention, dual attention, and self-attention.

The works mentioned above have several issues. The majority of studies use attention mechanisms at one level, either at the temporal or feature-level, ignoring a complete combination of the temporal, spatial/feature, and relational attention mechanisms in the same framework, which removes interdependencies of different types of signals. Using a single-head or other basic attention mechanism, it is impossible to influence the nuanced interactions of signals. Multi-head attention is dependent on parametric mechanisms, which increases computational costs and the potential for overfitting. Attention used for textual and numerical data limits their multi-modal learning in that they fail to integrate channel and spatial awareness at the same time.

To address these issues, the proposed approach incorporates a Modified Triple Attention mechanism into a hybrid CNN-RNN framework. By this method, the model can concentrate more effectively on the information that is necessary for prediction. Hence, the overall prediction reliability and accuracy are enhanced. Here, a basic RNN is used, as it provides a lower computational load compared to complex models such as GRU and LSTM. The proposed triple attention mechanism adaptively reweights temporal information, thereby reducing the need for additional gating mechanisms. Modified Triple Attention focuses on Channel Attention that tells which elements (channels) are important to the model. Spatial Attention tells the model where (in time or location) to focus. The triple attention mechanism enables deep multi-channel feature enhancement of what, where, and how much to attain, particularly appropriate for stock market forecasting, dynamically and flexibly.

3. Proposed Approach

The proposed system, MTA-HDCRNN, enhances stock market prediction accuracy by integrating the Modified Triple Attention Mechanism in a hybrid Deep Convolutional and Recurrent Neural Network. The input to the model is stock market data along with news. The more informative features from historical stock data are extracted. It includes statistical features, Entropy features, PCA features, and technical indicators.

3.1 MTA-HDCRNN System Model

The MTA-HDCRNN model's block diagram is depicted in Figure 1. The organized pre-processed data information is fed into the feature extraction phase. The output feature vector is created by concatenating all of the features, and it is then used as an input for the MTA-HDCRNN model. The output of the feature extraction phase forms the input for the MTA-HDCRNN model to predict the stock price. Input is fed to the DCNN phase, which is the combination of a convolutional layer and a max-pooling layer, which extracts local patterns from the data that is being input. The outcome of the DCNN phase is then fed to the RNN phase, which contains three simple RNNs. Sequential data is processed using an RNN. Data is passed onto the dropout layer after the RNN phase, where the attention mechanism is executed, and significantly improving performance.

3.2 Modified Triple Attention (MTA) Mechanism

The informative features of the data source are extracted automatically by the modified Triple attention mechanism, as shown in Figure 2, which contains a channel attention module and a spatial attention module. Based on these modules, the MTA performs the prediction process. Features have diverse spatial positions at every channel. Some of the channels contain effective spatial features, and some have smaller weighted modules with fewer spatial features. This feature information is accessed by the three-branch triple attention module, which captures the interaction of cross-dimensional information obtained from channel and spatial dimensions. The proposed triple attention mechanism integrates three corresponding branches. Channel × H-axis, Channel × W-axis, and H × W attention. It enables the model to choose where in the input space to focus as well as which features to emphasize. Merging all three branches results in richer representations and better interpretability. Removing any one branch limits the model's capacity to capture particular features or spatial dependencies.

There are three parallel branches for which the input is X, a stock feature tensor. Here $X \in R^{C \times H \times W}$, where channel dimension is denoted by C, and spatial dimensions are denoted by H (height) and W (width). Input is passed to all three branches. Eq. (1) illustrates the calculation process for the first branch,

$$X_{H+} = R^{H+}\left(X_H \, \sigma\left(Conv(Z\_pool(X_H))\right)\right) \qquad (1)$$

In this context, σ denotes the Sigmoid activation function, Conv is a standard convolutional operation, Z_pool is a pooling operation, and R^{H+} denotes a 90-degree clockwise rotation along the H axis. The attention weights are generated using the sigmoid activation function. Weighted feature maps are produced by applying the attention weights to feature parameters of the same width and then applying them to X_H. Finally, the input X is used to create an output X_{H+} that is identical in shape to the input X by rotating the weighted feature maps along the axis H by 90 degrees. Similarly, for the second branch, a calculation process is as given in Eq. (2) where R^{W+} represents a rotation of the W axis by 90 degrees clockwise

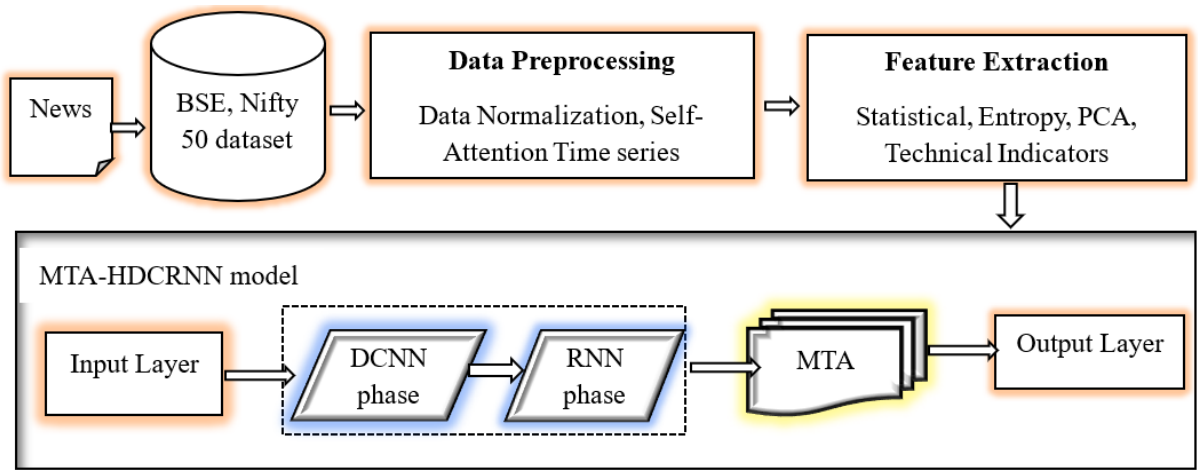

Figure 1. Block diagram for MTA-HDCRNN model

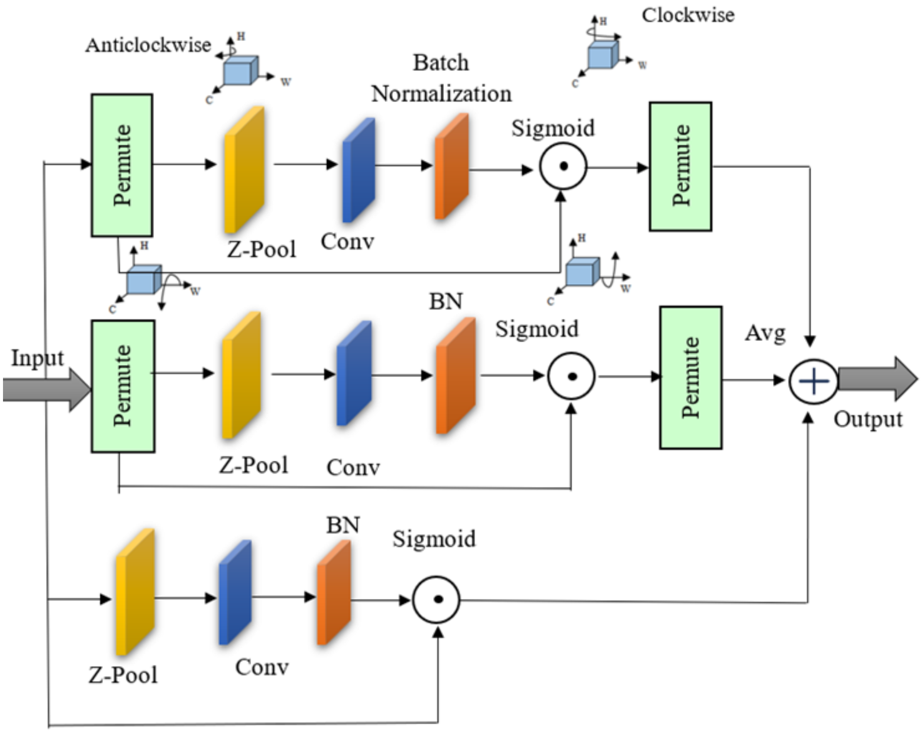

Figure 2. The architecture of the Modified Triple Attention mechanism

Algorithm: Triple Attention(X)

```
Input:
    X: Feature maps with dimensions (N, C, H, W)
    X^: Rotated feature map
Output:
    X_refined: Refined feature maps
// 1st Attention Branch
A ← Z pool (X^)                          // A has dimensions (N, C, H)
W_A ← Conv (A)                           // Apply convolution to A
W_A ← Sigmoid(W_A)                       // Normalize weights to [0, 1]
O_A ← ElementWiseMultiply (X, (W_A))     // Multiply original X with W_A
// 2nd Attention Branch
B ← Z pool (X^)                          // B has dimensions (N, C, W)
W_B ← Conv (B)                           // Apply convolution to B
W_B ← Sigmoid(W_B)                       // Normalize weights to [0, 1]
O_B ← ElementWiseMultiply (X, (W_B))     // Multiply original X with W_B
// 3rd Attention Branch
C ← Z pool (X)                           // C has dimensions (N, H, W)
W_C ← Conv (C)                           // Apply convolution to C
W_C ← Sigmoid(W_C)                       // Normalize weights to [0, 1]
O_C ← ElementWiseMultiply (X, (W_C))     // Multiply original X with W_C
// Aggregation: Combine outputs from all three branches
X_refined ← (O_A + O_B + O_C) / 3
Return X_refined
```

$$X_{W+} = R^{W+}\left(X_W\, \sigma\left(Conv\left(Z\_pool(X_W)\right)\right)\right) \qquad (2)$$

For the third branch, the original input tensor X is passed unchanged instead of being rotated to form the weighted feature map. It is shown in Eq. (3).

$$X_C = X\, \sigma\left(Conv\left(Z\_pool(X)\right)\right) \qquad (3)$$

The output from all three branches was aggregated to blend channel and spatial attention information as shown in Eq. (4).

$$Y = ((X_{H+} + X_{W+} + X_C)/3) \qquad (4)$$

This strategy ensures that the model gains the ability to highlight important spatial and channel characteristics. As a result, the performance of the deep learning model is improved. The following illustrates the Triple Attention mechanism's algorithm.

The comprehensive performance of the deep learning model is improved by the triple attention algorithm. It ensures that the model learns to concentrate on relevant spatial and channel features while emphasizing more important features.

4. Experimental Results

The experiment is carried out using the PyCharm software in a Windows 11 configuration with 16GB of RAM and 128GB of ROM. The experiment is performed on the Nifty 50 [24] and the BSE [25] datasets. Daily stock price details are obtained from the finance.yahoo.com website for 10 years, from 3/01/2014 to 3/31/2024. The news is also extracted using web scraping for BSE and Nifty 50 data [26]. Input data is refined in the preprocessing phase, which includes data normalization [27] and Self-Attention-Based Time Series (SATS) analysis [28]. News data are also refined using filtering and temporal imputation. Sentiment lexicon supports the sentiment analysis process. Additionally, a pre-trained sentiment analysis model such as VADER is used for automated sentiment scoring. These scores are then integrated into the feature set. Feature extraction is also performed using Statistical Features [29], Entropy Features [30-33], PCA Features [34], and Technical Indicators [35] to capture essential market patterns. The model is trained using k-fold cross-validation. K values range from 2 to 10. For model training, training set proportions of 40% to 80% are also considered, with a maximum of 100 epochs.

In this research, the attention heatmap is utilized to visualize the time series data changes over time and analyze the stock market variations, which is visualized based on colour intensity between green and red. The x-axis denotes the predicted date or time of a certain period, and the y-axis denotes the technical indicators that influence the stock market fluctuations, which is explained in the following Figure 3.

4.1 Modified Triple Attention performance evaluation

Various evaluation metrics are used for performance assessment of the MTA-HDCRNN model. Table 2 shows the performance evaluation of the MTA-HDCRNN model for the BSE dataset. For 80% training data, with epoch 100, the obtained error metric values are MAE 13.66, MSE 16.11, R^2 0.77, and RMSE 4.01. Similarly, for 10 K-fold cross-validation with epoch 100, MAE is 18.22, MSE is 23.45, R^2 is 0.68, and RMSE is 4.84.

The results of the performance evaluation of the MTA-HDCRNN model for the Nifty 50 dataset are presented in Table 3. For 80% training data with epoch 100, the obtained value for MAE is 12.57, MSE is 15.95, R^2 is 0.77, and RMSE is 3.99. For 10 K-Fold cross-validation with epoch 100, the achieved value for MAE is 18.20, MSE is 23.42, R^2 is 0.68, and RMSE is 4.84.

4.2 Comparison with Existing Models

The performance of the MTA-HDCRNN model is compared with the performance of the existing model. Table 4 illustrates the performance evaluation of the MTA-HDCRNN model with Linear Regression, CNN, LSTM, and BiLSTM [2] for the BSE dataset.

As shown in Table 4, the MTA-HDCRNN model is performing well among all other models according to all evaluation metrics. Here, the MTA-HDCRNN shows a difference of 4.08 in MAE, 4.08 in MSE, 0.08 in R^2, and 0.41 in RMSE as compared to Linear Regression. Similarly, for CNN, there is a difference of 2.08 in MAE, 2.07 in MSE, 0.04 in R^2, and 0.21 in RMSE. LSTM has a difference of 3.08 in MAE, 3.07 in MSE, 0.06 in R^2, and 0.31 in RMSE. Bi-LSTM is the nearest competitor; however, it shows a difference of 1.10, 1.10, 0.02, and 0.12 for MAE, MSE, R^2, and RMSE, respectively, against the MTA-HDCRNN model. The comparative evaluation analysis for different models is depicted in the following figures 4 to 7.

A statistical test (paired t-test) was applied to confirm that the improvement of the MTA-HDCRNN model performance is statistically significant. The MTA-HDCRNN model is compared with the baseline models across five thresholds for k-fold cross-validation for MAE results. The MTA-HDCRNN model continuously performed better than all baseline models, with statistically significant differences ($p < 0.05$).

Table 6 shows the results of evaluating the MTA-HDCRNN model with CNN, LSTM, BiLSTM, and Linear Regression on the Nifty 50 dataset.

According to all evaluation metrics, the MTA-HDCRNN model is outperforming all other models. In this case, the MTA-HDCRNN differs from Linear Regression by 4.08 in MAE, 4.07 in MSE, 0.08 in R^2, and 0.48 in RMSE. The differences for CNN are likewise 2.06

for MAE, 2.06 for MSE, 0.04 for R^2, and 0.25 for RMSE. The difference for LSTM is 3.07 for MAE, 3.07 for MSE, 0.06 for R^2, and 0.37 for RMSE. The closest competitor, Bi-LSTM, differs from the MTA-HDCRNN model by 1.10, 1.11, 0.02, and 0.14 for MAE, MSE, R^2, and RMSE, respectively.

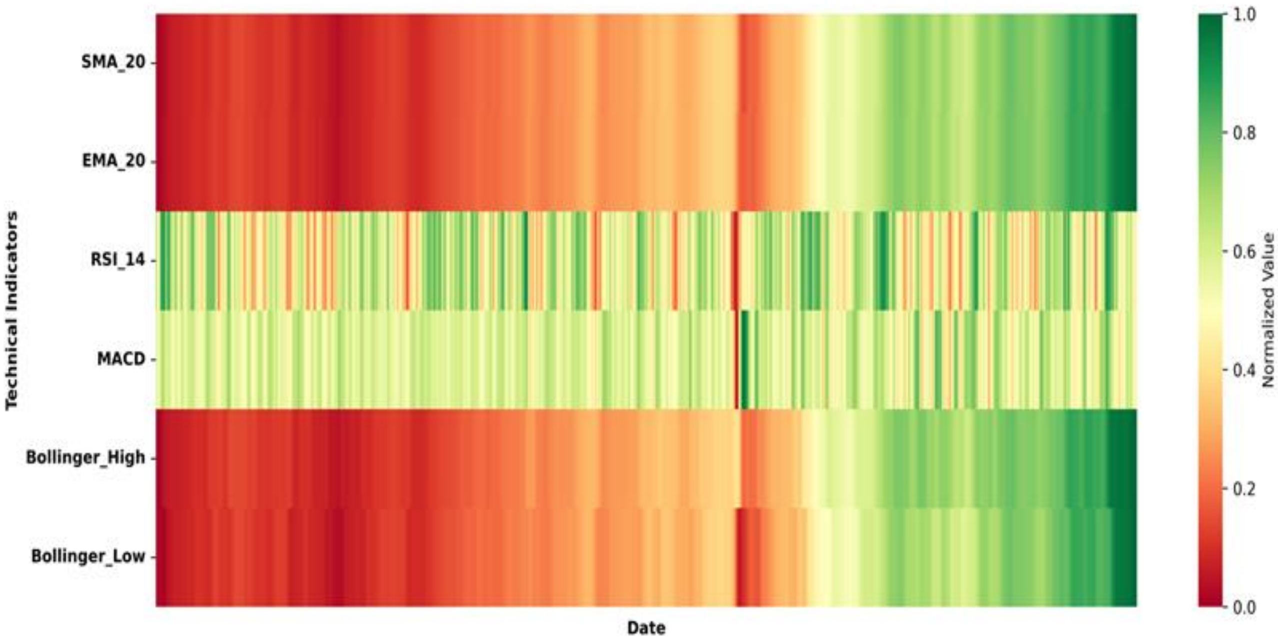

Figure 3. The attention heat map based on technical indicators

Table 2. Evaluation using Training% and k-fold for the BSE dataset

Metrics	BSE dataset									
	Training%					K-fold				
	40%	50%	60%	70%	80%	2	4	6	8	10
MAE	18.22	17.25	15.13	14.81	13.66	18.22	18.22	18.22	18.22	18.22
MSE	23.45	21.95	19.22	17.39	16.11	23.45	23.45	23.45	23.45	23.45
R^2	0.60	0.64	0.72	0.75	0.77	0.60	0.62	0.64	0.66	0.68
RMSE	4.84	4.68	4.38	4.17	4.01	4.84	4.84	4.84	4.84	4.84

Table 3. Evaluation using Training% and k-fold for the Nifty 50 dataset

Metrics	NIFTY 50 dataset									
	Training%					K-fold				
	40%	50%	60%	70%	80%	2	4	6	8	10
MAE	19.30	18.35	16.20	14.78	12.57	18.21	18.21	18.21	18.21	18.20
MSE	24.51	23.04	20.27	18.44	15.95	23.44	23.43	23.43	23.43	23.42
R^2	0.60	0.64	0.72	0.75	0.77	0.60	0.62	0.64	0.66	0.68
RMSE	4.95	4.80	4.50	4.29	3.99	4.84	4.84	4.84	4.84	4.84

Table 4. Performance Evaluation of MTA-HDCRNN Vs Existing Models

Methods/ dataset	BSE Dataset			
	K-Fold 10			
	MAE	MSE	R^2	RMSE
Linear-Regression	22.30	27.53	0.60	5.25
CNN	20.30	25.52	0.64	5.05
LSTM	21.30	26.52	0.62	5.15
BI-LSTM	19.32	24.55	0.66	4.96
MTA-HDCRNN	18.22	23.45	0.68	4.84

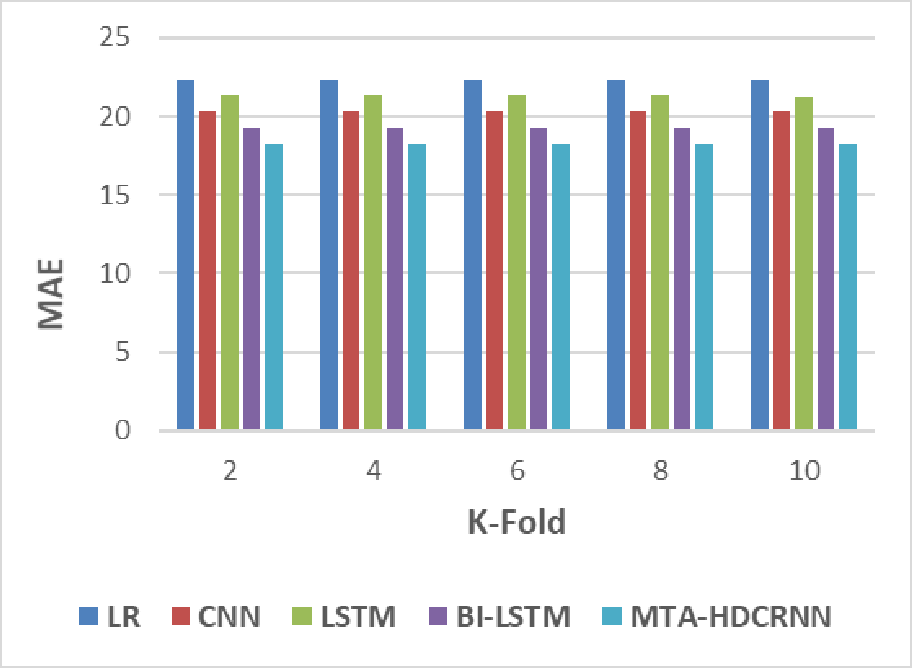

Figure 4. Comparative MAE analysis for BSE data

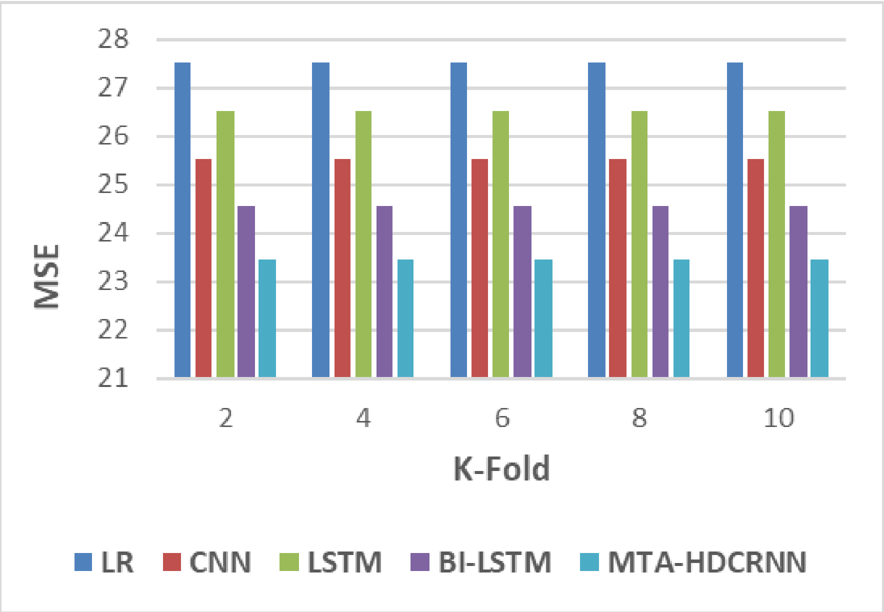

Figure 5. Comparative MSE analysis for BSE data

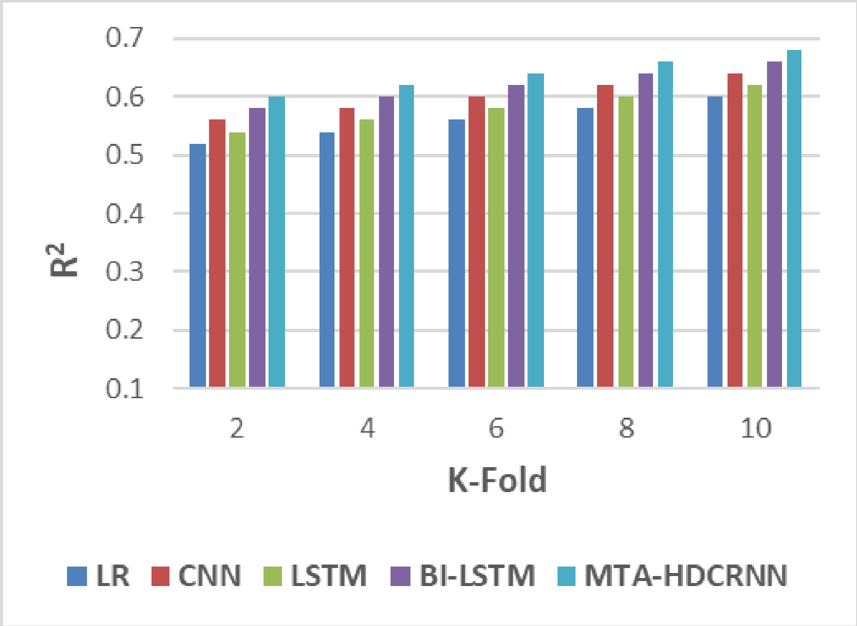

Figure 6. Comparative R2 analysis for BSE data

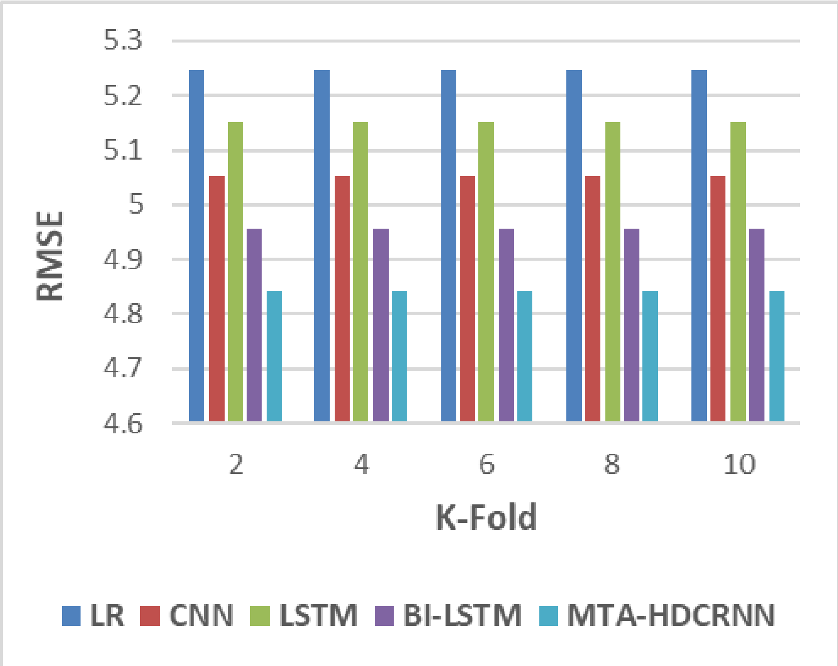

Figure 7. Comparative RMSE analysis for BSE data

Table 5. Statistical significance of MAE improvements using paired t-test

Methods	Mean (MAE)	Std. Dev.	t-statistic	p-value
Linear Regression	22.3069	0.0018	6288.38	3.84×10^{-15}
CNN	20.3054	0.0009	8155.10	1.36×10^{-15}
LSTM	21.3065	0.0020	5987.05	4.67×10^{-15}
BI-LSTM	19.3247	0.0005	4391.32	1.61×10^{-14}

Table 6. Performance Evaluation of MTA-HDCRNN for the Nifty 50 dataset

Methods/ dataset	Nifty 50 Dataset			
	80%			
	MAE	MSE	R^2	RMSE
Linear-Regression	16.65	20.02	0.69	4.47
CNN	14.63	18.01	0.73	4.24
LSTM	15.64	19.02	0.71	4.36
BI-LSTM	13.67	17.06	0.75	4.13
MTA-HDCRNN	12.57	15.95	0.77	3.99

5. Conclusion

This paper explored the MTA-HDCRNN mechanism. It is an integration of a Modified Triple Attention Mechanism into a Deep Convolutional and Recurrent Neural Network for stock price prediction. The MTA-HDCRNN enhances traditional deep learning architectures by incorporating spatial, channel, and identity attention mechanisms, ensuring that relevant features are emphasized while reducing redundant information. The triple attention mechanism learns the interdependences across different dimensions and effectively refines the feature map. This improves the ability of a model to find complex patterns in the data. Validation of a model is effectively done through experimentation on BSE and Nifty 50 datasets, and it is observed that the model performs better than the existing ones. The outcome for evaluation metrics MSE, MAE, RMSE, and R2 is 16.11, 13.66, 4.01, and 0.77, respectively. The key challenges in financial forecasting are addressed with this technique. It provides a more authentic, understandable, and efficient stock prediction framework. The investors and analysts can make improved trading decisions. They can better tackle the market risks. As far as a dynamic market is concerned, the blend of diversely sourced data with attention-based learning helps to improve circumstantial alertness. It helps in the formation of financial strategies and decision-making. The future work shall provide emphasis on strengthening the effectiveness of the deep learning model through vigorous optimization.

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Pranjali Kasture: Conceptualization, Methodology, Formal Analysis, Data Curation, Writing Original Draft. Kamini Shirsath: Conceptualization, Methodology, Supervision, Writing Original Draft, Writing Review & Editing. Both the authors read and approved the final version of this manuscript.

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes

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