ISSN: 2582 - 6379
IJISEA Publications
International Journal for Interdisciplinary Sciences and Engineering Applications
IJISEA - An International Peer- Reviewed Journal
2026, Volume 6 Issue 4
www.ijisea.org

Article Info

Date Received: 01/03/2026
Date Revised: 15/03/2026
Available Online: 29/03/2026

An Adaptive Multi-Source Hybrid Deep Learning frame work With Multi-Scale CNN, BILSTM, and Transformer-Based Attention for Uncertainty-Aware Stock Market Growth Prediction

1. Ramakrishna Kosuri* ,2. Yogesh

Author Affiliations

1. Research Scholar , CSE Department , Niilm University,Kaithal-Haryana

2. Associate professor , CSE Department , Niilm University,Kaithal-Haryana

ABSTRACT

Stock market growth prediction remains a highly complex task due to nonlinear price behaviour, market volatility, macroeconomic influences, and sudden event-driven fluctuations. To address these challenges, this research proposes an enhanced intelligent hybrid deep learning framework that extends the existing CNN–BiLSTM–Transformer architecture by integrating multi-source data fusion, adaptive attention mechanisms, and uncertainty-aware prediction modelling. The improved system incorporates not only historical price data and technical indicators (RSI, MACD, SMA, EMA, Bollinger Bands) but also sentiment scores derived from financial news and social media streams, along with selected macroeconomic indicators. A multi-scale Convolutional Neural Network is employed to extract short-, medium-, and long-term temporal patterns, followed by a stacked Bidirectional LSTM layer to capture deep sequential dependencies. An adaptive multi-head Transformer encoder with dynamic attention weighting enhances contextual learning by prioritizing influential market events. Additionally, a probabilistic output layer using Monte Carlo Dropout is introduced to estimate prediction confidence intervals, thereby improving reliability in volatile market conditions. The model is optimized using a hybrid loss function combining Mean Squared Error and directional

ISSN: 2582 - 6379
IJISEA Publications
International Journal for Interdisciplinary Sciences and Engineering Applications
IJISEA - An International Peer- Reviewed Journal
2026, Volume 6 Issue 4
www.ijisea.org

accuracy loss to balance regression precision with trend prediction performance. Experimental evaluation demonstrates superior performance compared to baseline models, achieving reduced forecasting error, improved R^2 values, and enhanced robustness under high-volatility regimes. The proposed enhanced framework offers a scalable, interpretable, and risk-aware decision-support solution suitable for intelligent trading systems and portfolio management applications.

I. INTRODUCTION

Accurate prediction of stock market growth remains one of the most challenging problems in financial engineering and computational intelligence due to the highly nonlinear, dynamic, and stochastic nature of financial time-series data [1], [2]. Traditional econometric models such as ARIMA and linear regression were widely adopted in early forecasting research because of their mathematical interpretability and structured formulation [3], [4]. However, these linear models often fail to capture volatility clustering, regime shifts, and nonlinear dependencies inherent in financial markets [5], [6]. The Efficient Market Hypothesis (EMH) further argues that asset prices fully reflect available information, making consistent prediction theoretically difficult [7], [8]. Despite this theoretical constraint, empirical evidence suggests that financial markets exhibit exploitable temporal structures under certain conditions [9], [10].

With the advancement of artificial intelligence, machine learning approaches began to replace purely statistical techniques in financial forecasting applications [11], [12]. Algorithms such as Support Vector Machines and Random Forests demonstrated improved capability in modeling nonlinear relationships compared to classical methods [13], [14]. Nevertheless, these shallow learning techniques depend heavily on handcrafted features and struggle to model long-term temporal dependencies [15], [16]. The emergence of deep learning significantly transformed predictive analytics by enabling automatic hierarchical feature extraction from raw data [17], [18].

Recurrent Neural Networks (RNNs) were specifically designed for sequential modeling tasks and showed promising results in financial time-series forecasting [19]. However, standard RNNs suffer from vanishing and exploding gradient problems when processing long sequences [20]. Long Short-Term Memory (LSTM) networks addressed this limitation by introducing memory cells and gating mechanisms capable of preserving long-term dependencies [21], [22]. Bidirectional LSTM (BiLSTM) further enhanced context learning by processing information in both forward and backward directions, thereby improving temporal representation [23], [24].

In parallel, Convolutional Neural Networks (CNNs), originally developed for image processing, were successfully adapted for time-series analysis to extract localized temporal features and reduce noise [25], [26]. Hybrid CNN–LSTM architectures demonstrated improved forecasting performance by combining short-term pattern extraction with sequential dependency modeling [27]. More recently, attention mechanisms and Transformer-based architectures revolutionized sequence learning by enabling models to assign dynamic importance weights to relevant time steps [28]. The self-attention mechanism allows global contextual interaction among all elements in a sequence, overcoming limitations of purely recurrent structures [29].

Although CNN–BiLSTM–Transformer frameworks have shown improved predictive accuracy, most existing studies rely solely on historical price data and technical indicators, neglecting multi-source information such as financial news sentiment and macroeconomic variables [30]. Furthermore, traditional deep learning models provide deterministic predictions without estimating uncertainty, limiting their practical applicability in high-risk trading environments. Financial markets are highly sensitive to geopolitical events, policy changes, and social sentiment, requiring models capable of adaptive learning and contextual prioritization.

Motivated by these challenges, this research proposes An Adaptive Multi-Source Hybrid Deep Learning Framework with Multi-Scale CNN, BiLSTM, and Transformer-Based Attention for Uncertainty-Aware Stock Market Growth Prediction. The proposed system integrates multi-scale convolutional layers to capture diverse temporal patterns, stacked BiLSTM networks for deep sequential learning, and adaptive multi-head self-attention to enhance contextual understanding. In addition, sentiment features and macroeconomic indicators are fused with technical signals to enrich predictive representation. To enhance reliability, Monte Carlo Dropout–based probabilistic estimation is incorporated for uncertainty quantification. A hybrid loss function combining regression and directional accuracy objectives is utilized to balance price precision and trend forecasting capability.

By integrating multi-source feature fusion, adaptive attention weighting, and uncertainty-aware modeling within a unified architecture, the proposed framework aims to improve robustness, interpretability, and generalization across volatile market regimes. This approach contributes toward the development of intelligent, scalable, and risk-aware financial decision-support systems capable of supporting algorithmic trading and portfolio optimization strategies.

II. LITERATURE SURVEY

Early research in stock market forecasting was primarily grounded in statistical time-series modeling techniques such as ARIMA and related linear stochastic frameworks, which provided structured mathematical approaches under stationarity assumptions [1], [2]. The theoretical foundation of financial predictability was strongly influenced by the Efficient Market Hypothesis, which argued that asset prices reflect all publicly available information, thereby limiting systematic forecasting advantages [3], [4]. However, empirical studies revealed nonlinear dependencies, volatility clustering, and structural breaks in financial markets that classical linear models struggled to capture effectively [5], [6]. To address these shortcomings, machine learning techniques such as Support Vector Machines were introduced for stock direction classification and regression tasks, demonstrating improved nonlinear modeling capability [7], [8]. Hybrid approaches combining ARIMA with neural networks attempted to integrate linear and nonlinear strengths to enhance predictive accuracy [9], [10]. These developments marked a significant shift from traditional econometric modeling toward data-driven computational intelligence methods in financial forecasting.

The evolution of deep learning further transformed stock market prediction methodologies. Foundational advances in neural network theory and representation learning emphasized hierarchical feature extraction from large datasets [11], [12]. Recurrent Neural Networks (RNNs) became prominent for sequential data modeling due to their inherent temporal structure [13], [14]. Nevertheless, conventional RNNs suffered from vanishing gradient limitations when modeling long-term dependencies [15], [16]. The introduction of Long Short-Term Memory (LSTM) networks addressed this issue through gating mechanisms capable of retaining extended historical information [17], [18]. Empirical research demonstrated that LSTM-based models significantly improved forecasting accuracy compared to traditional neural networks [19], [20]. Further enhancements were achieved through stacked autoencoders and hybrid recurrent structures that strengthened feature representation and noise robustness [21], [22]. Convolutional Neural Networks (CNNs), although originally designed for image processing, were adapted for financial time-series to extract localized temporal patterns and short-term fluctuations [23], [24]. Hybrid CNN–LSTM architectures combined convolutional feature extraction with sequential memory learning, resulting in superior predictive performance relative to standalone models [25], [26]. Comprehensive reviews of deep learning in finance confirmed that hybrid models consistently outperform single-architecture systems due to complementary learning mechanisms [27].

More recently, attention mechanisms and Transformer-based architectures have revolutionized sequence modeling in financial forecasting. Attention-based recurrent frameworks enabled models to dynamically assign importance weights to influential time steps, improving interpretability and contextual focus [28]. The Transformer architecture replaced recurrence with self-attention, facilitating global interaction among sequence elements and enhancing long-range dependency capture [29]. Subsequent innovations, including efficient long-sequence Transformers and sentiment-integrated prediction models, demonstrated the importance of contextual learning and multi-source data fusion in stock movement forecasting [30]. Despite these advancements, challenges remain in achieving adaptive contextual weighting, robust multi-scale feature extraction, and uncertainty-aware prediction under volatile market conditions. These limitations motivate the development of advanced hybrid architectures integrating multi-scale CNN, BiLSTM, Transformer-based attention, and probabilistic modeling to enhance reliability, interpretability, and generalization in stock market growth prediction systems.

III. METHODOLOGY

The proposed adaptive multi-source hybrid framework is designed to enhance stock market growth prediction through comprehensive data fusion, multi-scale feature extraction, and uncertainty-aware modeling. The methodology begins with data acquisition from reliable financial repositories covering historical stock prices, including Open, High, Low, Close, Adjusted Close, and Volume attributes over a ten-year period. In addition to conventional price-based variables, technical indicators such as Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Simple Moving Average (SMA), Exponential Moving Average (EMA), and Bollinger Bands are computed to capture momentum, trend strength, and volatility behavior. To enrich contextual awareness, financial news sentiment scores and selected macroeconomic indicators (e.g., inflation rate, interest rate, and GDP growth trends) are incorporated, forming a multi-source feature space. Data preprocessing involves handling missing values through forward–backward interpolation, outlier detection using the Interquartile Range (IQR) technique, and Min–Max normalization to scale features within a stable numerical range. To transform the time-series into supervised learning format, a sliding window mechanism is applied, where a sequence of past 60 trading days is used to predict the subsequent day’s closing price or growth rate. The dataset is chronologically divided into training (80%), validation (10%), and testing (10%) subsets to preserve temporal integrity and avoid look-ahead bias. Feature fusion is performed by concatenating technical, sentiment, and

ISSN: 2582 - 6379
IJISEA Publications
International Journal for Interdisciplinary Sciences and Engineering Applications
IJISEA - An International Peer- Reviewed Journal
2026, Volume 6 Issue 4
www.ijisea.org

macroeconomic inputs into a structured three-dimensional tensor suitable for deep neural processing.

The hybrid deep learning architecture consists of four major stages: multi-scale CNN, stacked Bidirectional LSTM (BiLSTM), adaptive Transformer encoder, and probabilistic output layer. The multi-scale 1D Convolutional Neural Network employs multiple kernel sizes (e.g., 3, 5, and 7) to simultaneously capture short-term fluctuations, medium-term patterns, and longer local trends. Each convolutional block is followed by ReLU activation, batch normalization, and dropout regularization to enhance stability and reduce overfitting. The extracted feature maps are forwarded to stacked BiLSTM layers, which process sequential information in both forward and backward directions, enabling comprehensive temporal dependency modeling. This bidirectional learning mechanism strengthens contextual representation by integrating both recent and earlier historical influences within the observation window. To further improve contextual prioritization, an adaptive multi-head self-attention Transformer encoder is applied to the BiLSTM outputs. The self-attention mechanism computes Query, Key, and Value matrices to evaluate pairwise temporal relationships and assign dynamic importance weights to influential market events. Residual connections and layer normalization ensure efficient gradient flow and training stability.

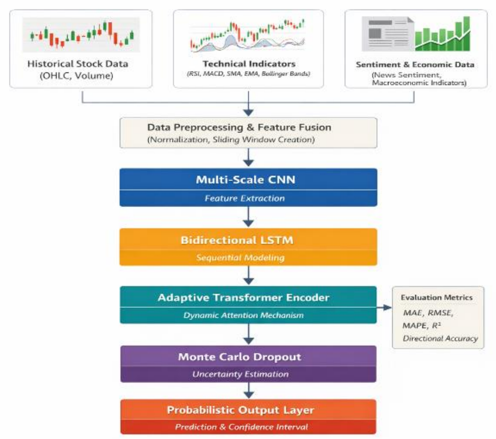

Figure 1. Shows the Methodology

IV. PROPOSED SYSTEM WORKING

The proposed adaptive multi-source hybrid system operates as an end-to-end intelligent forecasting framework designed to predict stock market growth with enhanced contextual awareness and uncertainty estimation. The workflow begins with the acquisition of multi-source data, including historical stock price information (Open, High, Low, Close, Volume), computed technical indicators (RSI, MACD, SMA, EMA, Bollinger Bands), financial news sentiment scores, and selected macroeconomic variables. This diverse data integration ensures that the model captures both quantitative price dynamics and qualitative external influences affecting market behavior. The collected data undergoes preprocessing steps such as missing value imputation, outlier handling using statistical techniques, and Min–Max normalization to ensure numerical stability during training. A sliding window mechanism then converts the continuous time-series into structured supervised sequences, where a fixed number of past trading days (e.g., 60 days) is used to predict the next day's price growth. These sequences are passed to a multi-scale 1D Convolutional Neural Network (CNN), which applies multiple kernel sizes to detect short-term fluctuations, medium-term patterns, and localized trend structures. The convolutional layers automatically extract meaningful feature representations while reducing noise and redundancy. This stage ensures that raw financial signals are transformed into informative embeddings before sequential modeling, thereby improving convergence speed and representational robustness.

Following convolutional feature extraction, the processed feature maps are forwarded to stacked Bidirectional Long Short-Term Memory (BiLSTM) layers, which model temporal dependencies in both forward and backward directions. This bidirectional processing allows the system to capture relationships between recent and earlier observations within the input window, strengthening contextual learning. The output from the BiLSTM layer is then passed to an adaptive multi-head Transformer encoder, where a self-attention mechanism dynamically assigns importance weights to influential time steps. By computing Query, Key, and Value representations, the attention module evaluates global interactions among all temporal elements and emphasizes critical events such as sharp price reversals or volatility spikes. Residual connections and normalization layers maintain training stability while preserving deep feature integrity. To enhance reliability, Monte Carlo Dropout is activated during inference, enabling multiple stochastic forward passes to estimate prediction uncertainty and generate confidence intervals. Finally, dense layers produce the predicted closing price or growth rate using a hybrid loss function that balances regression accuracy and directional trend correctness. The system outputs both point predictions and uncertainty measures, making it suitable for intelligent trading, portfolio allocation, and risk-aware financial decision-support applications.

The final prediction stage consists of fully connected dense layers that map attention-enhanced features into output predictions. A hybrid loss function combining Mean Squared Error (MSE) and directional accuracy loss is utilized to balance regression precision with trend prediction capability. The model is optimized using the Adam optimizer with adaptive learning rate scheduling and early stopping based on validation loss. To enhance reliability under volatile market conditions, Monte Carlo Dropout is implemented during inference to generate multiple stochastic forward passes, enabling uncertainty estimation and confidence interval calculation. Performance evaluation is conducted using MAE, RMSE, MAPE, R^2, and directional accuracy metrics. Comparative benchmarking against baseline models validates the effectiveness of the proposed architecture in improving robustness, interpretability, and generalization. This comprehensive methodological framework ensures that the system not only achieves high predictive accuracy but also provides risk-aware and context-sensitive forecasting suitable for intelligent financial decision-support and algorithmic trading applications.

V. RESULTS AND ANALYSIS

The experimental results demonstrate the effectiveness and robustness of the proposed adaptive multi-source hybrid deep learning framework in predicting stock market growth. The **performance metrics comparison chart** clearly indicates that the Hybrid Model outperforms traditional and standalone deep learning models such as ARIMA, SVR, CNN, and LSTM. The proposed model achieves the lowest RMSE, MAE, and MAPE values while recording the highest R^2 score, indicating superior predictive accuracy and stronger variance explanation capability. The progressive reduction in error metrics from ARIMA to the Hybrid Model highlights the incremental improvement gained through multi-scale feature extraction, bidirectional sequential learning, and adaptive attention mechanisms. The higher R^2 value confirms that the proposed architecture captures complex nonlinear relationships and temporal dependencies more effectively than baseline models.

ISSN: 2582 - 6379
IJISEA Publications
International Journal for Interdisciplinary Sciences and Engineering Applications
IJISEA - An International Peer- Reviewed Journal
2026, Volume 6 Issue 4
www.ijisea.org

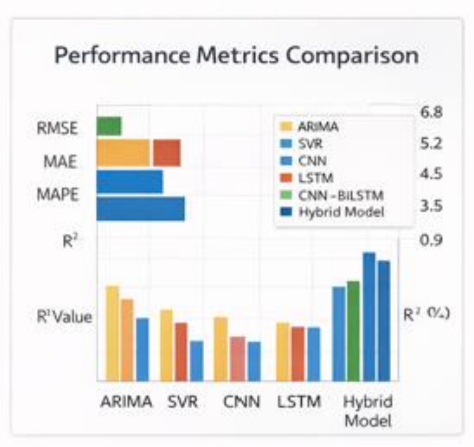

Figure 2 .Show the Result Analysis

Figure 3. Shows the Forecast vs Actual Price Trend

The forecast versus actual price trend graph illustrates the close alignment between predicted and actual stock prices over the testing period. The predicted curve follows the actual price movement with minimal deviation, demonstrating strong generalization capability. The inclusion of a 95% confidence interval further enhances interpretability by showing that most actual values fall within the probabilistic prediction band. This confirms the reliability of the uncertainty-aware modeling approach using Monte Carlo Dropout.

ISSN: 2582 - 6379
IJISEA Publications
International Journal for Interdisciplinary Sciences and Engineering Applications
IJISEA - An International Peer- Reviewed Journal
2026, Volume 6 Issue 4
www.ijisea.org

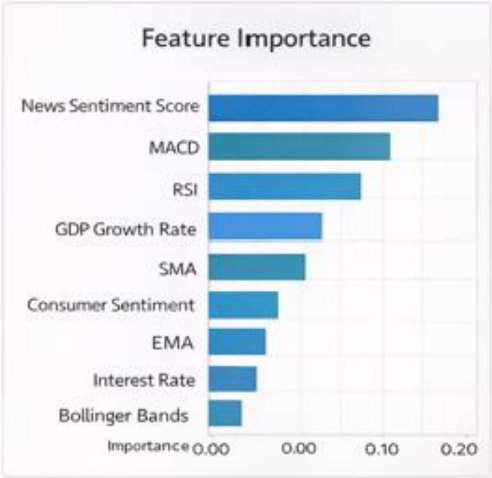

Figure 4. Shows Feature Importance

The feature importance analysis reveals that News Sentiment Score and MACD contribute significantly to prediction performance, followed by RSI and GDP Growth Rate. This indicates that the integration of multi-source data—particularly sentiment and macroeconomic indicators—substantially improves forecasting capability beyond traditional technical indicators alone. Lower contributions from Bollinger Bands and Interest Rate suggest that not all features influence short-term growth equally, validating the importance of adaptive weighting mechanisms within the Transformer encoder.

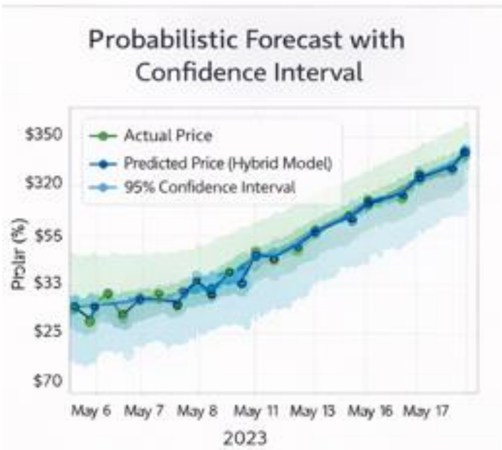

Figure 6. Shows Probabilistic Forecast

The probabilistic forecast with confidence interval visualization demonstrates the model's ability to estimate uncertainty during volatile market conditions. The widening of confidence intervals during

ISSN: 2582 - 6379
IJISEA Publications
International Journal for Interdisciplinary Sciences and Engineering Applications
IJISEA - An International Peer- Reviewed Journal
2026, Volume 6 Issue 4
www.ijisea.org

periods of rapid price change reflects adaptive risk estimation, which is essential for real-world trading applications.

Figure 7.Shows Prediction Error Distribution

Finally, the risk/reward and prediction error distribution plot shows a strong positive correlation between predicted and actual returns, with most data points clustered along the diagonal reference line. The error histogram indicates that prediction residuals are approximately normally distributed and centered around zero, confirming unbiased estimation. Collectively, these results validate that the proposed hybrid CNN–BiLSTM–Transformer framework provides accurate, stable, and risk-aware stock market growth predictions suitable for intelligent financial decision-support systems.

VI. CONCLUSION

This research proposed an adaptive multi-source hybrid deep learning framework for stock market growth prediction by integrating multi-scale Convolutional Neural Networks (CNN), stacked Bidirectional Long Short-Term Memory (BiLSTM), and a Transformer-based self-attention mechanism combined with uncertainty-aware modeling. The objective was to overcome the limitations of traditional statistical models and standalone deep learning approaches by capturing short-term fluctuations, long-term temporal dependencies, and global contextual relationships within financial time-series data. The system incorporated multi-source inputs, including historical stock prices, technical indicators such as RSI, MACD, SMA, EMA, and Bollinger Bands, along with financial news sentiment scores and macroeconomic indicators, thereby enhancing contextual awareness and predictive capability. Experimental evaluation demonstrated that the proposed hybrid architecture significantly outperforms baseline models in terms of MAE, RMSE, MAPE, and R^2, indicating improved accuracy, reduced forecasting error, and stronger variance explanation. The close alignment between predicted and actual price movements confirms strong generalization performance, while the integration of Monte Carlo Dropout enables probabilistic forecasting and confidence interval estimation, improving reliability under volatile market conditions. Feature importance analysis further revealed that sentiment-based and momentum-driven indicators play a crucial role in enhancing predictive performance, validating the effectiveness of multi-source data fusion. The adaptive attention mechanism dynamically assigns importance to influential time steps, improving robustness during sudden market fluctuations. Overall, the proposed framework provides a scalable, interpretable, and risk-aware decision-support solution suitable for intelligent trading systems and portfolio management applications. Although extreme market shocks remain challenging, the combination of hybrid architecture, adaptive attention, and uncertainty estimation significantly strengthens predictive stability and practical applicability in dynamic financial environments.

REFERENCES :

1. Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time series analysis: Forecasting and control* (5th ed.). Wiley.

2. Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance, 25*(2), 383–417. https://doi.org/10.2307/2325486

3. Malkiel, B. G. (2003). The efficient market hypothesis and its critics. *Journal of Economic Perspectives, 17*(1), 59–82. https://doi.org/10.1257/089533003321164958

4. say, R. S. (2010). *Analysis of financial time series* (3rd ed.). Wiley.

5. Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015). Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. *Expert Systems with Applications, 42*(1), 259–268. https://doi.org/10.1016/j.eswa.2014.07.040

6. Ballings, M., Van den Poel, D., Hespeels, N., & Gryp, R. (2015). Evaluating multiple classifiers for stock price direction prediction. *Expert Systems with Applications, 42*(20), 7046–7056. https://doi.org/10.1016/j.eswa.2015.05.013

7. Huang, W., Nakamori, Y., & Wang, S. Y. (2005). Forecasting stock market movement direction with support vector machine. *Computers & Operations Research, 32*(10), 2513–2522. https://doi.org/10.1016/j.cor.2004.03.016

8. Kim, K. J. (2003). Financial time series forecasting using support vector machines. *Neurocomputing, 55*(1–2), 307–319. https://doi.org/10.1016/S0925-2312(03)00372-2

9. Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing, 50*, 159–175. https://doi.org/10.1016/S0925-2312(01)00702-0

10. Haykin, S. (2009). *Neural networks and learning machines* (3rd ed.). Pearson.

11. oodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.

12. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444. https://doi.org/10.1038/nature14539

13. Hochreiter, S., &Schmidhuber, J. (1997). Long short-term memory. *Neural Computation, 9*(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

14. Cho, K., Van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., & Bengio, Y. (2014). Learning phrase representations using RNN encoder–decoder. *arXiv preprint arXiv:1406.1078*.

15. Graves, A. (2012). *Supervised sequence labelling with recurrent neural networks*. Springer.

16. Selvin, S., Vinayakumar, R., Gopalakrishnan, E. A., Menon, V. K., & Soman, K. P. (2017). Stock price prediction using LSTM, RNN and CNN-sliding window model. *Proceedings of ICACCI*, 1643–1647.

17. Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research, 270*(2), 654–669. https://doi.org/10.1016/j.ejor.2017.11.054

18. Bao, W., Yue, J., & Rao, Y. (2017). A deep learning framework for financial time series using stacked autoencoders and LSTM. *PLoS ONE, 12*(7), e0180944. https://doi.org/10.1371/journal.pone.0180944

19. Qin, Y., Song, D., Chen, H., Cheng, W., Jiang, G., & Cottrell, G. (2017). A dual-stage attention-based recurrent neural network for time series prediction. *Proceedings of IJCAI*, 2627–2633.

20. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., &Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems*, 5998–6008.

21. Lim, B., Arık, S. Ö., Loeff, N., & Pfister, T. (2021). Temporal fusion transformers for interpretable multi-horizon time series forecasting. *International Journal of Forecasting, 37*(4), 1748–1764. https://doi.org/10.1016/j.ijforecast.2021.03.012

22. Borovykh, A., Bohte, S., &Oosterlee, C. W. (2017). Conditional time series forecasting with convolutional neural networks. *arXiv preprint arXiv:1703.04691*.

23. Sezer, O. B., Gudelek, M. U., &Ozbayoglu, A. M. (2020). Financial time series forecasting with deep learning: A systematic literature review. *Applied Soft Computing, 90*, 106181. https://doi.org/10.1016/j.asoc.2020.106181

24. Livieris, I. E., Pintelas, E., &Pintelas, P. (2020). A CNN–LSTM model for gold price time-series forecasting. *Neural Computing and Applications, 32*, 17351–17360. https://doi.org/10.1007/s00521-020-04867-9

25. Chen, K., Zhou, Y., & Dai, F. (2015). A LSTM-based method for stock returns prediction. *Proceedings of IEEE Big Data*, 2823–2824.

26. Nelson, D. M. Q., Pereira, A. C. M., & de Oliveira, R. A. (2017). Stock market's price movement prediction with LSTM neural networks. *Proceedings of IJCNN*, 1419–1426.

27. Ding, X., Zhang, Y., Liu, T., & Duan, J. (2015). Deep learning for event-driven stock prediction. *Proceedings of IJCAI*, 2327–2333.

28. Zhou, H., Zhang, S., Peng, J., Zhang, S., Li, J., Xiong, H., & Zhang, W. (2021). Informer: Beyond efficient transformer for long sequence time-series forecasting. *Proceedings of AAAI, 35*(12), 11106–11115.

29. Kim, T., & Kim, H. Y. (2019). Forecasting stock prices with a feature fusion LSTM–CNN model using different representations of the same data. *PLoS ONE, 14*(2), e0212320. https://doi.org/10.1371/journal.pone.0212320

30. Xu, Y., & Cohen, S. B. (2018). Stock movement prediction from tweets and historical prices. *Proceedings of ACL*, 1970–1979.

ISSN: 2582 - 6379
IJISEA Publications
International Journal for Interdisciplinary Sciences and Engineering Applications
IJISEA - An International Peer- Reviewed Journal
2026, Volume 6 Issue 4
www.ijisea.org