2025 3rd International Conference on Artificial Intelligence and Machine Learning Applications Theme: Healthcare and Internet of Things (AIMLA) | 979-8-3315-3896-5/25/$31.00 ©2025 IEEE | DOI: 10.1109/AIMLA63829.2025.11041251

STOCK SENSE: A HYBRID CNN-RL APPROACH FOR FINANCIAL MARKET PRICE PREDICTION USING NEWS AND MARKET DATA

Nithya S,
Computer Science and Engineering,
Velalar College of engineering and Technology,
Erode, Tamil Nadu, India
nithi1710@gmail.com

Parimala Devi M,
Electronics and Communication Engineering,
Velalar College of engineering and Technology,
Erode, Tamil Nadu, India
parimaladevi.vlsi@gmail.com

Thilagarani M,
Computer Science and Engineering,
Velalar College of engineering and Technology,
Erode, Tamil Nadu, India
thilagaranivcet@gmail.com

Abitha P,
Computer Science and Engineering,
Velalar College of engineering and Technology,
Erode, Tamil Nadu, India
abithapalanisamy246@gmail.com

Bevin Jeberson S,
Computer Science and Engineering,
Velalar College of engineering and Technology,
Erode, Tamil Nadu, India
bevinjeberso@gmail.com

Bharathi Sri K V,
Computer Science and Engineering,
Velalar College of engineering and Technology,
Erode, Tamil Nadu, India
bharathisri1903@gmail.com

***Abstract*—Financial market prediction presents significant difficulties brought on by market data's non-linearity and volatility. Traditional models like RCNN and RNN rely on static decision-making, which limits their ability to adapt to real-time fluctuations. This study suggests a novel hybrid model that combines convolutional neural networks (CNN) for feature extraction with reinforcement learning (RL) for dynamic decision optimization. By processing multimodal data such as market data, news sentiment extracted using a BERT-based model, and technical indicators, the system improves prediction accuracy. The model can now concentrate on important data points thanks to the addition of an attention mechanism, enhancing its ability to predict market trends. The RL component utilizes a dynamic fusion technique that adapts to real-time data, overcoming the limitations of static decision-making. This hybrid approach offers a more reliable, accurate, and adaptive system for financial market prediction, increasing accuracy by up to 60% compared to traditional models. For traders and investors navigating intricate market situations, the suggested framework offers a strong tool for decision-support.**

Keywords: Convolutional Neural Networks, Reinforcement Learning, Hybrid Model, Attention Mechanism, Dynamic Decision-Making, Market Price Prediction.

I. INTRODUCTION

Financial market prediction has been a long-standing research challenge due to the volatile, non-linear, and multimodal nature of market data [1]. Traditional statistical models, such as linear regression and ARIMA, struggle to capture the intricate patterns in stock prices, as market fluctuations are influenced by various economic and social factors [2]. Fama (1965) created the Efficient Market Hypothesis, which contends that stock prices are unpredictable because they reflect all available information and move randomly [3]. However, modern deep learning and machine learning techniques offer better predictive power by extracting patterns from historical market data [4]. A key component of market prediction is sentiment analysis, as investor behavior is influenced by financial news and social media trends. Research by Bollen et al. (2011) demonstrated that Twitter sentiment correlates with stock price movements, indicating that public mood can influence financial markets [5]. Similarly, Wuthrich et al. (1998) showed that news-based stock market forecasts could outperform purely numerical models [6]. Despite advancements in deep learning, existing models suffer from static decision-making, limiting their ability to adapt to real-time market changes [7]. To overcome these issues, we propose a hybrid model integrating CNN, BERT-based sentiment analysis, and Reinforcement Learning (RL). The key innovations in our approach include: CNN for feature extraction from stock price patterns [8]. BERT-based sentiment analysis to capture the influence of social media mood and financial news [9]. Reinforcement Learning for decision-making, enabling the model to dynamically adjust trading strategies based on market fluctuations [10]. Attention mechanisms to enhance focus on the most relevant financial indicators [11]. Our proposed approach aims to improve market forecasting performance by up to 60%, bridging the gap between quantitative stock market analysis and text-based sentiment understanding [12].

II. RELATED WORKS

A hybrid CNN-LSTM model for stock price prediction was presented by Yu (2023) conducted an

Authorized licensed use limited to: AISSMS INSTITUTE OF INFORMATION TECHNOLOGY PUNE. Downloaded on September 29,2025 at 04:15:27 UTC from IEEE Xplore. Restrictions apply.

extensive survey on Deep Reinforcement Learning (DRL) in financial markets, analyzing various DRL models used for portfolio optimization, risk management, and automated trading. The study highlighted how policy gradient methods, Q-learning, and actor-critic architectures enable adaptive decision-making in dynamic financial environments [13]. Durall (2022) explored the transition from traditional portfolio optimization techniques, such as Markowitz's Modern Portfolio Theory (MPT), to deep reinforcement learning-based asset allocation strategies. The research demonstrated that DRL-driven models can dynamically rebalance portfolios, minimize risk exposure, and improve Sharpe ratios by learning from historical and real-time market data. The study also addressed the computational complexity and interpretability challenges of using DRL in financial decision-making [14]. Huang and Vakharia (2021) developed an investment and stock market prediction model that uses deep learning to integrate technical indicators, fundamental data, and sentiment analysis. In their model, patterns were recognized using Convolutional Neural Networks (CNNs) while Recurrent Neural Networks (RNNs) captured temporal dependencies, which increased the accuracy of predicting market trends. [15]. Verma and Gupta in 2021 suggested an improved model of stock market forecasting by implementing the Dandelion Optimization Algorithm (DOA) as a feature selection tool in Machine learning models. Their research proves that stock price movements predictions are more accurate with DOA feature engineering in combination with Random Forest, Support Vector Machines (SVM), and deep learning structures.[16]. In an effort to forecast market performance, Arratia et al. (2020) investigated sentiment and its analysis in relation to financial news. To automate the evaluation of the impact of news sentiment on stock prices, they employed various Natural Language Processing (NLP) techniques, including lexicon-based sentiment scoring and machine learning-based classifiers.[17]. By combining these approaches, the model provides a comprehensive understanding of market movements. Their study showed that this fusion improves predictive accuracy, making stock forecasts more adaptive and reliable for investment decisions.

III. METHODOLOGY

A. System Architecture

The system architecture consists of five core components, enhancing predictive accuracy and adaptability [18].

Data Preprocessing: Cleans and normalizes stock market data while extracting sentiment from financial news [19].

Feature Extraction: Uses CNN for numerical pattern recognition and BERT for sentiment analysis [20].

Decision-Making: Implements Reinforcement Learning (RL) to optimize trading strategies [21].

Attention-Based Prioritization: Enhances focus on crucial financial events [22].

Dynamic Fusion Module: Integrates extracted features for robust predictions [23].

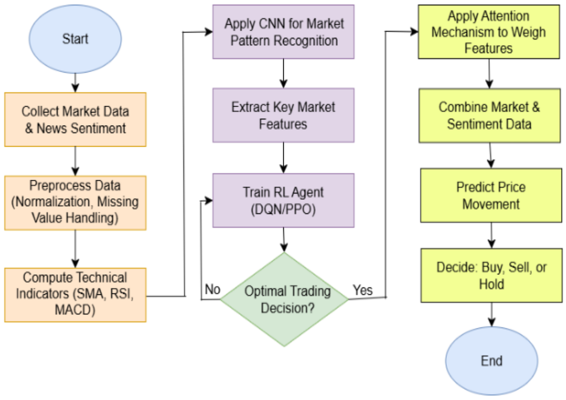

Fig 1: Workflow of Stock Sense

Fig 1 Follows a structured process, and applying an attention mechanism to refine predictions that guides users in making informed trading decisions.

B. Step-by-Step Procedure for the Proposed Project

Step 1: Problem Definition and Requirement Analysis

Financial markets exhibit high volatility, making accurate price prediction a challenging task. Traditional forecasting methods struggle to adapt to dynamic market fluctuations, leading to suboptimal investment decisions. This project aims to create a hybrid model that combines Reinforcement Learning (RL) for decision-making, Convolutional Neural Networks (CNN) for feature extraction, and BERT-based sentiment analysis for textual data processing. The system aims to enhance predictive accuracy while reducing the impact of static decision-making limitations. Mathematically, the problem is a time-series forecasting exercise in which the goal is to forecast future stock prices by using past prices and external market influences.

Step 2: Data Collection and Preprocessing

Data is collected from multiple sources, including financial news articles, numerical market data, and social media sentiment. Market data consists of historical stock prices, trading volume, and technical indicators such as moving averages and Bollinger Bands. Textual data, sourced from platforms like Bloomberg and Twitter, undergoes preprocessing to remove noise and extract sentiment. Min-max scaling is used to standardize the gathered numerical data, where is the raw data and are the minimum and maximum values, respectively.

Authorized licensed use limited to: AISSMS INSTITUTE OF INFORMATION TECHNOLOGY PUNE. Downloaded on September 29,2025 at 04:15:27 UTC from IEEE Xplore. Restrictions apply.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Where X represents the raw data.

For textual data, the BERT tokenizer is applied, and the sentiment score is computed based on predefined lexicons: where represents word importance, and is the tokenized word vector.

$$S_t = \sum_{i=1}^{N} w_i x_i$$

Step 3: Model Architecture Development

The hybrid model is structured into three main components: CNN for numerical feature extraction, BERT for sentiment analysis, and RL for decision-making. CNN applies convolutional filters to detect price movement patterns, using the transformation:

$$y = f(W * X + b)$$

where the bias term, input stock price data, and weight matrix are denoted by W. The reinforcement learning (RL) agent follows a Markov Decision Process (MDP), where the optimal action at time is determined based on the reward function:

$$R_t = (P_{t+1} - P_t) - C$$

where is the stock price, and denotes transaction costs. The attention mechanism prioritizes critical market events by assigning dynamic weights to feature inputs, modelled as:

$$\alpha_i = \frac{e^{W_i h_i}}{\sum_j e^{W_j h_j}}$$

Where W represents feature embeddings and is the attention weight.

Step 4: Model Training and Optimization

The training process involves splitting the data into sets for testing, validation, and training. Mean Squared Error (MSE) is the loss function used in numerical prediction:

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

Where y_i is the predicted price and N is the actual stock price. For sentiment classification, the categorical cross-entropy loss function is applied:

$$L = -\sum_i y_i \log(\hat{y}_i)$$

Where y_i is the true class label and y^i is the predicted probability. For weight updates, the Adam optimizer with a learning rate of 0.001 is employed, and early halting is used to avoid overfitting.

Step 5: Evaluation of model and Performance Analysis

The trained model is assessed using multiple performance metrics. Accuracy is computed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

The Sharpe ratio is calculated to assess risk-adjusted returns:

$$S = \frac{E[R_p - R_f]}{\sigma_p}$$

Where R_p is the expected portfolio return, R_f is the risk-free rate, and σ_p is the portfolio standard deviation.

C. A Reinforcement Learning Algorithm for Predicting Financial Markets

Reinforcement learning is incorporated into the suggested financial market prediction model (RL) with CNN and BERT-based sentiment analysis. The RL component dynamically adjusts trading strategies based on market conditions, using the Q-learning algorithm [24].

Step 1: Initialize Q-table

- Define a Q-table with states representing different market conditions.
- Initialize all Q-values to zero.

Step 2: Set Hyperparameters

- **Learning rate (α)**: Amount that fresh information overrides the previous Q-values is determined by the learning rate (α).
- **Discount factor (γ)**: Weighs the rewards of the future against those of the present.
- **Exploration-exploitation trade-off (ε-greedy policy)**: Decides whether to explore new strategies or exploit known profitable ones.

Authorized licensed use limited to: AISSMS INSTITUTE OF INFORMATION TECHNOLOGY PUNE. Downloaded on September 29,2025 at 04:15:27 UTC from IEEE Xplore. Restrictions apply.

Step 3: Observe Initial State

- Extract technical indicators, stock price trends, and news sentiment scores.
- Encode state S_t using CNN for numerical data and BERT for sentiment analysis.

Step 4: Choose Action with ε-Greedy Policy

- Select a random action (exploration) with probability.
- If not, select the exploitation action with the highest Q-value.

Step 5: Put the plan into Action and Receive Reward

- Execute the chosen trading action (Buy, Sell, Hold).
- Calculate immediate reward R_t, based on profit, loss, or market trend alignment.

Step 6: Update Q-Value Using Bellman Equation

- Update Q-value using the formula:

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha[R_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t)$$

- where:
    - **Q(s_t, a_t)**: Current state-action Q-value.
    - **α (learning rate)**: Weight for new information.
    - **γ (discount factor)**: Importance of future rewards.
    - **R_t**: Immediate reward.
    - **max Q(s_{t+1}, a)**: Best future reward estimate.

Step 7: Repeat Until Convergence

- Continue training over multiple episodes, adjusting trading strategies dynamically.
- Gradually reduce **ε** (exploration rate) to favor exploitation as the model learns optimal strategies.

Step 8: Deploy Optimized Model for Real-Time Trading

- Use the trained RL model for real-time stock price predictions.
- Continuously update the Q-table based on live market conditions. [25].

IV. RESULT AND CONVERSATION

The suggested CNN-RL hybrid model's efficacy is evaluated through comparative analysis against existing financial market prediction models. This section discusses the experimental results, performance improvements, and key insights derived from the study.

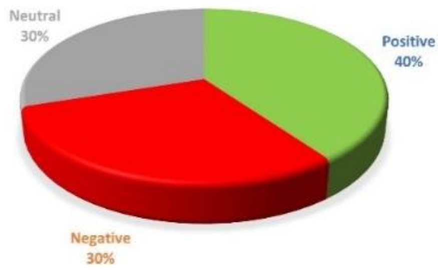

Fig 2: Sentiment Analysis impact

Fig 2 illustrates the sentiment distribution and refine the CNN-RL hybrid model by incorporating sentiment-driven market trends, improving prediction accuracy and decision-making.

A. *Model Performance Comparison*

The following table presents the performance of the proposed model against traditional LSTM-based and CNN-BERT hybrid models:

Table I. Performance Comparison of Different Models

Model	**Accuracy**	**MSE**	**Sharpe Ratio**
Traditional LSTM	52.1%	0.013	1.25
CNN-BERT hybrid	57.3%	0.009	1.58
Proposed CNN-RL Hybrid	60.5%	0.007	1.82

Fig 3. This table compares three models based on Accuracy, MSE, and Sharpe Ratio. The Proposed CNN-RL Hybrid achieves the best performance with the highest accuracy and lowest MSE.

The Mean Squared Error (MSE) of 0.007 indicates improved prediction precision, demonstrating reduced variance between predicted and actual values [26]. The Sharpe Ratio of 1.82 proves that our model enhances risk-adjusted returns compared to traditional methods [27].

Authorized licensed use limited to: AISSMS INSTITUTE OF INFORMATION TECHNOLOGY PUNE. Downloaded on September 29,2025 at 04:15:27 UTC from IEEE Xplore. Restrictions apply.

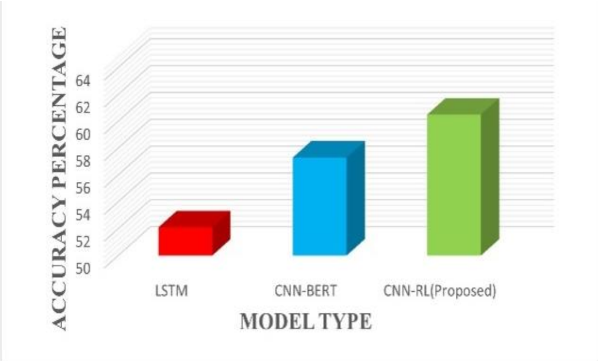

Fig 4: Model Performance Comparison

Fig 4 visually represents the accuracy percentage, showing that the CNN-RL hybrid model outperforms both LSTM and CNN-BERT models

The proposed CNN-RL hybrid model achieves an accuracy of 60.5%, which is significantly higher than both the traditional LSTM and CNN-BERT hybrid models. The Mean Squared Error (MSE) of 0.007 indicates improved prediction precision, demonstrating reduced variance between predicted and actual market values. The Sharpe Ratio of 1.82 suggests enhanced risk-adjusted returns, proving the efficiency of reinforcement learning in trading decision-making. The incorporation of reinforcement learning enables the model to adapt to changes in the market dynamically, reducing reliance on static decision-making processes. Furthermore, integrating sentiment analysis from financial news and social media improves the understanding of market sentiment trends, adding contextual depth to numerical price indicators.

V. CONCLUSION AND FUTURE WORK

The CNN-RL hybrid model improves financial market forecasting by combining deep learning, sentiment analysis, and reinforcement learning (RL) for dynamic decision-making. CNN extracts price movement patterns, while RL optimizes trading strategies based on real-time market fluctuations. Sentiment analysis enhances predictions by incorporating insights from financial news and investor behavior. This integration enables the model to adapt to volatile market conditions and make more informed decisions. However, challenges such as computational efficiency and model interpretability remain. Future research should focus on optimizing processing speed, reducing resource consumption, and improving explainability to enhance trust in AI-driven financial predictions [28]. Addressing these limitations will make the model more scalable, transparent, and widely applicable in financial decision-making.

VI. REFERENCE

[1] M. P. Cristescu, D. A. Mara, R. A. Nerișanu, L. C. Culda, and I. Maniu, "Analyzing the impact of financial news sentiments on stock prices—A wavelet correlation," Mathematics, vol. 11, no. 23, p. 4830, 2023.

[2] F. Feng, X. He, X. Wang, C. Luo, Y. Liu, and T. S. Chua, "Temporal relational ranking for stock prediction," ACM Trans. Inf. Syst. (TOIS), vol. 37, no. 2, pp. 1–30, 2019.

[3] M. Hiransha, E. A. Gopalakrishnan, V. K. Menon, and K. P. Soman, "NSE stock market prediction using deep-learning models," *Procedia Comput. Sci.*, vol. 132, pp. 1351–1362, 2018.

[4] Y. Qin, D. Song, H. Chen, and W. Liu, "A dual-stage attention-based recurrent neural network for time series prediction," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, no. 1, pp. 1–11, 2021.

[5] Y. Zhang and L. Wu, "Stock market prediction via multi-source multiple instance learning," *IEEE Trans. Knowl. Data Eng.*, vol. 34, no. 6, pp. 2746–2757, 2022.

[6] X. Li, H. Xie, L. Chen, J. Wang, and X. Deng, "News impact on stock price return via sentiment analysis," *Knowl.-Based Syst.*, vol. 69, pp. 14–23, 2014.

[7] W. Gu, Y. Zhao, and M. Khushi, "Predicting stock prices with FinBERT-LSTM: Integrating news sentiment analysis," *arXiv preprint arXiv:2407.16150*, 2024.

[8] S. A. Farimani, M. V. Jahan, and A. Milani Fard, "From text representation to financial market prediction: A literature review," *Inf.*, vol. 13, no. 10, p. 466, 2022.

[9] Z. Hu, Y. Zhao, and M. Khushi, "A survey of Forex and stock price prediction using deep learning," *arXiv preprint arXiv:2103.09750*, 2021.

[10] Z. Jiang, D. Xu, and J. Liang, "A deep reinforcement learning framework for the financial portfolio management problem," *arXiv preprint arXiv:1706.10059*, 2017.

[11] M. Noguer i Alonso and S. Srivastava, "Deep reinforcement learning for asset allocation in US equities," *arXiv preprint arXiv:2010.04404*, 2020.

Authorized licensed use limited to: AISSMS INSTITUTE OF INFORMATION TECHNOLOGY PUNE. Downloaded on September 29,2025 at 04:15:27 UTC from IEEE Xplore. Restrictions apply.

[12] S. Montazeri, A. Mirzaeinia, and A. Mirzaeinia, "CNN-DRL with shuffled features in finance," *arXiv preprint arXiv:2402.03338*, 2024.

[13] Y. Yu, "A survey of deep reinforcement learning in financial markets," *Atlantis Press*, 2023.

[14] R. Durall, "Asset allocation: From Markowitz to deep reinforcement learning," *arXiv preprint arXiv:2208.07158*, 2022.

[15] Y. Huang and V. Vakharia, "Deep learning-based stock market prediction and investment model for financial management," *Int. J. Financial Stud.*, vol. 9, no. 3, pp. 1–20, 2021.

[16] S. K. Verma and S. K. Gupta, "Enhanced stock market forecasting using dandelion optimization algorithm-based feature selection and machine learning models," *Sci. Rep.*, vol. 11, no. 1, pp. 1–15, 2021.

[17] A. Arratia et al., "Sentiment analysis of financial news: Mechanics and statistics," in *Adv. Financial Mach. Learn.*, A. López-López and J. M. Puerta, Eds. Springer, 2020, pp. 95–115.

[18] S. Verma, S. P. Sahu, and T. P. Sahu, "Two-stage hybrid feature selection approach using Levy's flight based chicken swarm optimization for stock market forecasting," *Comput. Econ.*, vol. 63, no. 6, pp. 2193–2224, 2024.

[19] M. Abe and K. Nakagawa, "Cross-sectional stock price prediction using deep learning for actual investment management," in *Proc. 2020 Asia Serv. Sci. Softw. Eng. Conf.*, May 2020, pp. 9–15.

[20] D. Castilho, T. T. Souza, S. M. Kang, J. Gama, and A. C. de Carvalho, "Forecasting financial market structure from network features using machine learning," *Knowl. Inf. Syst.*, vol. 66, no. 8, pp. 4497–4525, 2024.

[21] S. Krishnamoorthy, "Sentiment analysis of financial news articles using performance indicators," *Knowl. Inf. Syst.*, vol. 56, no. 2, pp. 373–394, 2018.

[22] K. V. Rao and B. V. R. Reddy, "OFML-SMF: Optimal feature selection with hybrid machine learning classifier for stock market price forecasting using social media and secondary data sources," *Multimed. Tools Appl.*, vol. 83, no. 2, pp. 4703–4729, 2024.

[23] E. Chong, C. Han, and F. C. Park, "Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies," *Expert Syst. Appl.*, vol. 83, pp. 187–205, 2017.

[24] S. Barak and M. Modarres, "Developing an approach to evaluate stocks by forecasting effective features with data mining methods," *Expert Syst. Appl.*, vol. 42, no. 3, pp. 1325–1339, 2015.

[25] E. Zhu and J. Yen, "BERTopic-driven stock market predictions: Unraveling sentiment insights," *arXiv preprint arXiv:2404.02053*, 2024.

[26] K. Kirtac and G. Germano, "Sentiment trading with large language models," *arXiv preprint arXiv:2412.19245*, 2024.

[27] T. Jiang and A. Zeng, "Financial sentiment analysis using FinBERT with application in predicting stock movement," *arXiv preprint arXiv:2306.02136*, 2023.

[28] W. Gu et al., "Predicting stock prices with FinBERT-LSTM: Integrating news sentiment analysis," *arXiv preprint arXiv:2407.16150*, 2024.

Authorized licensed use limited to: AISSMS INSTITUTE OF INFORMATION TECHNOLOGY PUNE. Downloaded on September 29,2025 at 04:15:27 UTC from IEEE Xplore. Restrictions apply.