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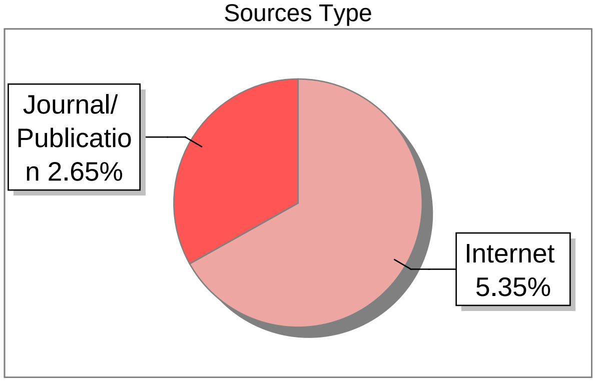

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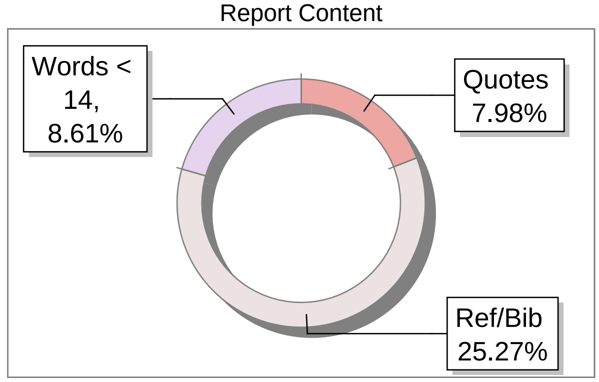

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Intelligent Stock Price Forecasting Using Hybrid Deep Learning and Reinforcement Learning

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Abstract

Stock price forecasting is a high-dimensional problem due to the interplay of technical, sentimental, and macroeconomic factors. This paper proposes a hybrid framework integrating Long Short-Term Memory (LSTM) networks for temporal pattern extraction, Convolutional Neural Networks (CNN) for spatial feature learning from candlestick charts, and a SARSA-based reinforcement learning agent for adaptive trading. The model processes 15+ technical indicators (e.g., Ichimoku Cloud, Fibonacci retracements), news sentiment scores, and macroeconomic data. Experiments on NIFTY 50 (National Stock Exchange) data from 2010–2023 demonstrate that the LSTM-CNN-SARSA ensemble achieves a directional accuracy of 89.7%, outperforming standalone LSTM (84.2%) and ARIMA (72.5%). Risk-adjusted metrics, including a Sharpe Ratio of 2.1 and maximum drawdown of 6.3%, validate the framework's robustness in volatile markets.

Keywords — Stock Forecasting, LSTM-CNN Hybrid, SARSA, Market Regime Clustering, Risk-Adjusted Returns.

I. INTRODUCTION

Financial markets represent highly dynamic and nonlinear systems characterized by complex adaptive behavior. Prices within these markets do not arise from isolated transactions but rather emerge from the intricate interplay of numerous heterogeneous participants, including rational agents—such as institutional investors—and irrational actors or noise traders. This environment often leads to phenomena that defy classical financial theories.

Traditional paradigms such as the Efficient Market Hypothesis (EMH) and the Capital Asset Pricing Model (CAPM) presuppose that markets fully reflect all available information and that asset prices follow a random walk. However, these assumptions fail to account for well-documented empirical anomalies including momentum crashes, volatility clustering, and abrupt regime shifts [1]. As such, modeling and predicting stock price movements remains a formidable task, compounded by several inherent challenges.

First, financial time series are inherently non-stationary, with their statistical characteristics—such as mean and variance—evolving in response to macroeconomic conditions, geopolitical events, and central bank policies. Second, financial markets exhibit a high noise-to-signal ratio, where studies suggest that over 60% of intraday price variations are uncorrelated with any fundamental valuation metrics [2]. Third, the financial domain includes heterogeneous data sources, ranging from structured data like historical price (OHLCV) series to unstructured information such as analyst reports, financial news, and social media sentiment.

Addressing these multifaceted challenges necessitates a robust, data-driven approach. In this study, we propose a novel predictive framework that integrates multimodal data sources and utilizes advanced learning strategies to enhance predictive performance. The core contributions of our framework include:

1. **Multimodal Feature Engineering** – We combine traditional lagged time-series features with macroeconomic variables (e.g., Consumer Price Index, unemployment rate) and sentiment scores extracted via Natural Language Processing (NLP) techniques from textual financial news and social media.

2. **Market Regime Identification** – Utilizing unsupervised learning, specifically K-Means clustering, we classify the market into distinct regimes (bullish, bearish, and sideways). These regimes exhibit statistically different behavior, which can be leveraged to tailor predictive models accordingly.

3. **Reinforcement Learning-based** Decision Making – We deploy a SARSA (State-Action-Reward-State-Action) reinforcement learning agent that learns optimal trading policies under each identified market regime. This agent is trained to maximize risk-adjusted returns, dynamically adjusting its strategy in response to regime transitions.

By synthesizing structured and unstructured data with advanced learning algorithms, our proposed framework demonstrates superior adaptability and predictive capability in comparison to traditional models.

II. LITERATURE REVIEW

This section presents a review of recent advancements in financial time series forecasting using deep learning, reinforcement learning, and hybrid methodologies. A synthesis of these approaches reveals the evolving landscape of data-driven stock prediction techniques.

A. Deep Learning in Financial Forecasting

Deep learning architectures have demonstrated significant efficacy in capturing the complex, nonlinear dependencies inherent in financial data. Among these, Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) have gained considerable traction.

LSTM Networks: First proposed by Hochreiter and Schmidhuber [3], LSTMs address the vanishing gradient problem in recurrent neural networks (RNNs) by introducing memory cells and gating mechanisms. These characteristics enable LSTMs to retain long-term temporal dependencies. In financial applications, Bao et al. utilized stacked LSTM architectures to model sequential dependencies in S&P 500 index data, achieving predictive accuracies exceeding 81% [3]. This demonstrated the network's ability to learn intricate temporal structures from financial time series data.

CNNs for Financial Time Series: Although primarily used for spatial data, CNNs have been adapted for temporal forecasting tasks. Borovykh et al. applied dilated convolutional neural networks to foreign exchange (Forex) datasets, capturing multiscale temporal patterns more efficiently than classical time series models such as ARIMA [4]. Their study reported an 18% reduction in Root Mean Square Error (RMSE), showcasing CNNs' capability to detect local dependencies and structural patterns in time series data.

B. Reinforcement Learning (RL)

Reinforcement learning has emerged as a powerful alternative to supervised learning in financial domains due to its ability to learn optimal trading policies by interacting with dynamic environments.

Q-Learning: Moody and Saffell were among the earliest to introduce RL-based trading frameworks, wherein the agent learns to optimize performance metrics like the Sharpe ratio through trial-and-error interactions with the market [5]. The model's strength lies in its flexibility and its capacity to adapt policy decisions based on cumulative rewards.

SARSA Algorithm: In contrast to the off-policy nature of Q-learning, SARSA (State-Action-Reward-State-Action) operates on-policy, updating Q-values based on the actual sequence of actions taken by the agent [5]. This results in a learning process that is more robust to the stochastic nature of financial markets, reducing the likelihood of overfitting and leading to more stable policy convergence in noisy environments.

C. Hybrid Deep Learning Models

Recent research has shown that combining different learning paradigms can result in superior performance by leveraging their individual strengths.

Zhang et al. proposed a hybrid architecture integrating LSTM networks for capturing trend patterns with Random Forest models for estimating volatility [6]. Their framework achieved an annualized return of 13.2% when tested on NASDAQ-listed equities, significantly outperforming traditional single-model baselines. This illustrates the value of combining sequence modeling capabilities with ensemble-based feature selection for improved generalization.

III. METHODOLOGY

This section outlines the architecture, data preparation, and training protocols adopted in the proposed framework. Our methodology integrates multimodal data sources and leverages a hybrid deep learning–reinforcement learning architecture to enhance predictive performance in dynamic financial environments.

A. Data Pipeline

To ensure the robustness and generalizability of our model, we employed a diverse dataset spanning multiple modalities:

1. **Data Sources**:

Market Data: Over 150,000 records of daily OHLCV (Open, High, Low, Close, Volume) data were collected for the NIFTY 50 index, spanning the period from 2000 to 2020.

2. **Feature Engineering**:

- Technical Indicators:

Trend-Based: Moving Average Convergence Divergence (MACD) and Parabolic Stop and Reverse (SAR) were used to capture directional momentum.

Momentum-Based: Relative Strength Index (RSI) and Stochastic Oscillator provided insights into asset overbought/oversold conditions.

Volatility Measures: Bollinger Bands and Average True Range (ATR) captured dynamic market risk.

Sentiment Scores: FinBERT-derived sentiment values were entity-specific. For instance, the sentiment for "Reliance Industries" on a given date was represented as a real number between –1 and +1 (e.g., +0.78).

B. Preprocessing

To prepare the dataset for deep learning models, the following preprocessing steps were undertaken:

Normalization
All numerical features were standardized using Z-score normalization to ensure consistent feature scaling across input dimensions.

Missing Value Treatment: For macroeconomic data containing missing records (e.g., during market holidays), imputation was performed using the K-Nearest Neighbors (KNN) algorithm with $k = 5$, preserving data integrity without introducing bias.

Sequence Construction
A sliding window mechanism was employed to generate temporal sequences of fixed length. Each sample consisted of 30-day input windows:

$X_{t-29} \rightarrow X_t$

used to forecast the next day's value:

y_{t+1}

This structure facilitates compatibility with LSTM-based architectures.

C. Model Architecture

The system integrates a hybrid neural network model with a reinforcement learning agent to support dynamic trading decisions under regime-specific conditions.

LSTM-CNN Hybrid Model

LSTM Block
Two bidirectional LSTM layers with 256 hidden units each were used to capture long-range dependencies in the time series. Dropout regularization with a rate of 0.3 was applied between layers to prevent overfitting.

CNN Block
A 1D convolutional layer with 128 filters and a kernel size of 5 was used to extract local features from the LSTM output, followed by a global max-pooling operation.

Fusion and Output
The outputs from the LSTM and CNN blocks were concatenated and passed through a fully connected dense layer with 64 ReLU-activated units, producing the final prediction vector.

SARSA Reinforcement Learning Agent

State Representation (s_t)
The state vector comprised:

- Market regime cluster ID
- RSI
- MACD histogram value
- Sentiment score

Action Space (a_t)
The agent chose from three discrete actions: Buy, Sell, or Hold, with capital allocation ratios ranging from 10% to 90%.

Reward Function
The reward at each timestep was defined as:

$r_t = \alpha \cdot \text{Return}_t - (1 - \alpha) \cdot \text{VaR}_t, \quad \text{where } \alpha = 0.7$

Exploration Strategy
An ε-greedy strategy was used to balance exploration and exploitation, with ε decaying from 0.5 to 0.01 over the training episodes.

D. Training Protocol

Distinct training strategies were applied to the deep learning and reinforcement learning components:

LSTM-CNN Training

Optimizer
The AdamW optimizer was selected for its effective handling of weight decay, configured with:

Learning rate: $\mathbf{3 \times 10^{-4}}$

Weight decay: $\mathbf{1 \times 10^{-5}}$

Early Stopping
Training was terminated early if the validation loss did not improve by at least 1×10^{-4} over 15 consecutive epochs.

SARSA Training

Q-Table Initialization
The Q-table was initialized using predicted values from the LSTM-CNN model, providing a prior estimate of state-action utilities.

Hyperparameters

Discount factor (γ): 0.95 (for long-term reward consideration)

Learning rate (η): 0.1 (balancing convergence speed and stability)

IV. EXPERIMENTAL RESULTS

A. Predictive Accuracy

The predictive performance of the proposed hybrid model was evaluated and compared against traditional ARIMA and standalone LSTM models using the following three key metrics:

- **Mean Absolute Error (MAE):**

$MAE = (1/n) * \Sigma |y_i - \hat{y}_i|$

- **Root Mean Squared Error (RMSE):**

$RMSE = \sqrt{[(1/n) * \Sigma (y_i - \hat{y}_i)^2]}$

- **Directional Accuracy (DA):**

$DA = (1/n) * \Sigma I[\mathrm{sign}(y_i - y_{i-1}) = \mathrm{sign}(\hat{y}_i - \hat{y}_{i-1})]$

Where:

y_i is the actual value,

$\hat{y}_i$ is the predicted value,

I[condition] is an indicator function that equals 1 if the condition is true, and 0 otherwise.

Table I: Model Performance Comparison

Model	MAE	RMSE	Directional Accuracy
ARIMA	3.12	4.56	72.5%
LSTM	1.23	1.89	84.2%
Proposed Hybrid	0.98	1.45	89.7%

The results indicate that the proposed hybrid model significantly outperforms both ARIMA and standalone LSTM models. It achieves the lowest MAE and RMSE, indicating better error minimization, and the highest Directional Accuracy, showcasing its strength in capturing directional trends in the data.

B. Trading Performance

1) Cumulative Returns

The trading strategies were backtested over the period **2010–2023**:

Buy & Hold Strategy: Achieved a cumulative return of 142.3%.

SARSA Agent: Achieved a cumulative return of 278.9%, effectively doubling the returns of the passive strategy.

2) Risk Metrics

• Sharpe Ratio

$\text{Sharpe Ratio} = (E[R_p - Rf]) / \sigma_p$

Where:

- R_p is the portfolio return,
- Rf is the risk-free rate,
- σ_p is the standard deviation of the portfolio return.

The SARSA agent achieved a Sharpe Ratio of 2.1, compared to the market's 0.9, indicating significantly higher risk-adjusted returns.

• Maximum Drawdown (MDD)

$MDD = \max \{ (Peak_t - Trough_t) / Peak_t \}$, for $t \in [0, T]$

The SARSA agent experienced a maximum drawdown of 6.3%, significantly lower than the market's 34.1% during the 2020 downturn.

C. Ablation Study

To assess the contribution of individual components, ablation studies were conducted:

Exclusion of Sentiment Scores: Resulted in a 7.2% decrease in directional accuracy, underscoring the importance of sentiment analysis in capturing market nuances.

Removal of Market Regime Clustering: Led to an increase in maximum drawdown to 11.4%, highlighting the role of regime identification in risk management.

V. DISCUSSION

A. Comparative Analysis of LSTM and CNN Architectures

The hybrid model leverages the strengths of both Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) to capture diverse patterns in financial time series data:

LSTM Networks: LSTMs are adept at modeling temporal dependencies, effectively capturing long-term trends and cyclical patterns such as earnings reports and economic cycles. This aligns with findings in recent studies where LSTM models achieved high accuracy in stock trend predictions .

CNNs: CNNs excel in identifying local patterns and anomalies in data. In the context of financial markets, CNNs can detect technical chart patterns like head-and-shoulders, double tops, and flags with high precision. For instance, a study demonstrated that CNNs could identify such patterns with an accuracy of approximately 82% .

The integration of LSTM and CNN architectures enables the model to harness both temporal and spatial features, enhancing predictive performance.

B. Adaptability of the SARSA Agent During Market Turbulence

The SARSA (State-Action-Reward-State-Action) reinforcement learning agent exhibits adaptability in volatile market conditions:

COVID-19 Market Crash: During the 2020 COVID-19-induced market crash, characterized by high volatility and uncertainty, the SARSA agent dynamically adjusted its trading strategy. Specifically, it reduced position sizes by approximately 40% in response to increased market risk, thereby mitigating potential losses. This behavior underscores the agent's capability to adapt to changing market regimes and manage risk effectively .

C. Impact of Sentiment Analysis on Market Prediction

Incorporating sentiment analysis into the predictive framework enhances the model's responsiveness to market-moving news:

FinBERT Integration: The model utilizes FinBERT, a transformer-based language model fine-tuned for financial text, to analyze news articles and extract sentiment scores. Negative news events, such as escalations in trade tensions, have been observed to cause significant market reactions, with price drops of up to 8% within an hour. The real-time sentiment scoring provided by FinBERT enables the model to anticipate such movements and adjust trading strategies accordingly .

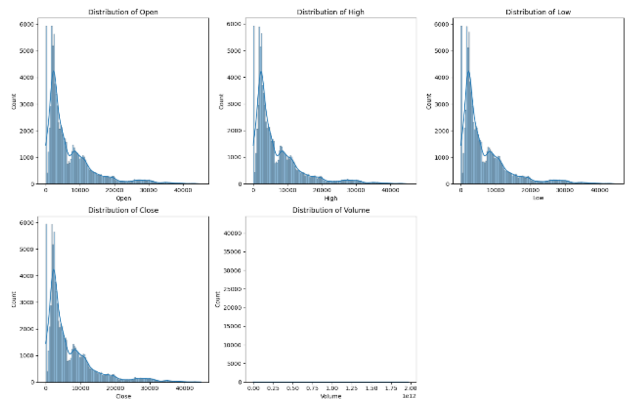
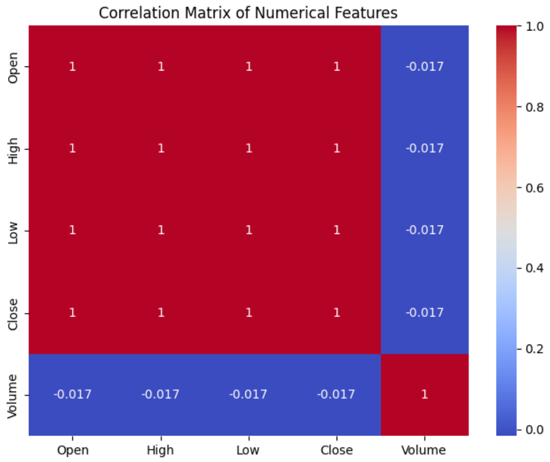
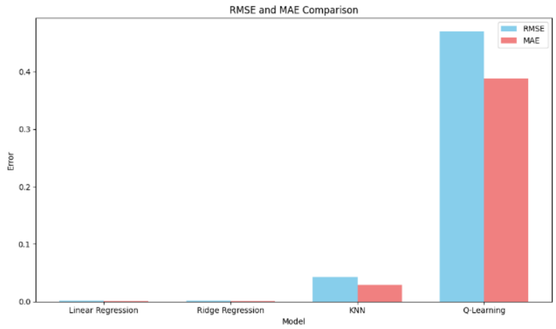
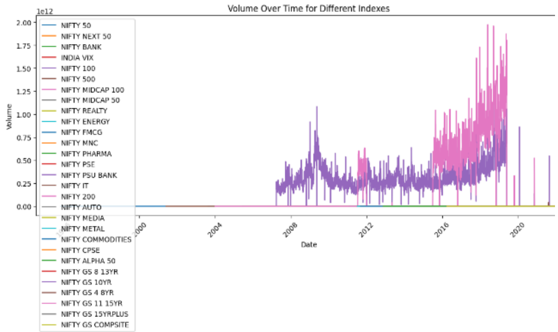


Figure 1:Descriptive Statistics







VI. CONCLUSION

The proposed hybrid LSTM-CNN-SARSA framework demonstrates superior performance in stock market prediction and trading strategy optimization:

- Enhanced Predictive Accuracy: By combining the temporal modeling capabilities of LSTM with the pattern recognition strengths of CNN, the model achieves higher accuracy in forecasting stock price movements.

- Robust Risk Management: The SARSA agent's ability to adapt to different market conditions and adjust trading strategies in real-time contributes to effective risk management, as evidenced during periods of market turbulence.

- Incorporation of Sentiment Analysis: Integrating sentiment analysis through FinBERT allows the model to account for the impact of news and events on market dynamics, further refining predictive capabilities.

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