NeuroStock: A Deep Learning Framework for Stock Market Forecasting with Web-Based Analytics

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Abstract: ***Stock market prediction is challenging due to its volatile, nonlinear nature. NeuroStock is a deep learning framework using Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and Hybrid CNN-LSTM models to predict stock prices over 7–60 days. It processes real-time Yahoo Finance data and evaluates performance with metrics like RMSE, MAE, R^2, Directional Accuracy, and Precision. A Streamlit web app lets users select stocks, tweak settings, view predictions, and compare models. Tests on GOOG stock show the Hybrid CNN-LSTM model balances accuracy (RMSE: 9.218274, R^2: 0.913406), while LSTM minimizes errors (RMSE: 4.413391). Unlike prior studies, NeuroStock excels in model comparison, trend prediction, and user-friendly deployment. It offers real-time insights for investors and analysts. Future updates, like sentiment analysis and additional data inputs, will boost accuracy, making NeuroStock a powerful tool for financial forecasting.***

Keywords: Deep Learning, Stock Market Prediction, LSTM, CNN, Hybrid CNN-LSTM, Streamlit, Yahoo Finance, Time-Series Forecasting, Directional Metrics, Web Deployment

1. Introduction

The stock market, characterized by its volatile, nonlinear, and dynamic behavior, has long captivated researchers and investors seeking to predict future price movements [1]. Accurate forecasting is challenging due to the interplay of numerous factors, including historical pricing patterns, trading volumes, macroeconomic indicators, and external events such as geopolitical shifts or corporate announcements [2]. Traditional statistical models like ARIMA often fail to capture the complex, non-stationary patterns in financial time-series data, prompting a shift toward machine learning (ML) and deep learning (DL) techniques that excel in modeling nonlinearity and temporal dependencies [3], [4].

This work introduces NeuroStock, an innovative deep learning framework designed to forecast stock prices and empower investors with actionable insights. NeuroStock leverages three advanced architectures—Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and a Hybrid CNN-LSTM model—to predict stock prices over customizable horizons ranging from 7 to 60 days. By integrating LSTM's ability to capture long-term dependencies, CNN's strength in extracting local patterns, and the hybrid model's combined feature extraction and temporal learning, NeuroStock addresses the multifaceted nature of financial data [5], [6]. The framework uses real-time data sourced from the Yahoo Finance API (yfinance), ensuring access to comprehensive historical records and up-to-date market information.

NeuroStock evaluates model performance using a robust set of metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-squared (R^2), Directional Accuracy, and Directional Precision. These metrics provide a holistic assessment, capturing both numerical accuracy and the practical utility of predicting price movement directions, a critical aspect for investment decisions often overlooked in prior work [6], [7]. To enhance usability, NeuroStock is deployed as an interactive Streamlit web application, allowing users to select stock tickers, adjust model parameters (e.g., lookback period, epochs), visualize predictions, and compare model performance in real time. This deployment bridges the gap between complex AI models and practical financial tools, addressing the lack of user-friendly interfaces in existing studies [2].

The primary objectives of NeuroStock are twofold: (1) to develop a predictive system that achieves high accuracy across short- and long-term forecasts, and (2) to provide an accessible platform for investors and analysts to derive investment insights. Preliminary results on GOOG stock demonstrate the Hybrid CNN-LSTM model's balanced performance (RMSE: 7.1635, R^2: 0.9472), with LSTM excelling in error minimization (RMSE: 4.8546) [8]. Despite its strengths, NeuroStock currently relies on historical price data, and future enhancements, such as sentiment analysis from news or social media, could further improve accuracy during event-driven market shifts [1], [2].

NeuroStock's contributions include:
1) A comparative analysis of LSTM, CNN, and Hybrid CNN-LSTM models, leveraging their complementary strengths.
2) Comprehensive evaluation using error and directional metrics, addressing gaps in trend prediction.
3) Real-time deployment via a Streamlit app, enhancing accessibility and interactivity.
4) A scalable framework with potential for integrating sentiment analysis and multivariate inputs.

This paper is organized as follows: Section II reviews related work, Section III details the methodology, Section IV describes the implementation, Section V presents results and discussion, and Section VI concludes with future directions.

2. Literature Review

Stock market prediction has been a focal point of financial analytics, evolving from statistical models to advanced machine learning (ML) and deep learning (DL) techniques over the past decade [2]. The complexity of financial time-series data, characterized by nonlinearity, volatility, and external influences, necessitates robust predictive models [3]. This section provides a comprehensive review of 15 seminal studies, organized into five thematic subsections: (1) Traditional Machine Learning Approaches, (2) Deep Learning with LSTM and RNN, (3) Convolutional Neural Networks, (4) Hybrid and Ensemble Models, and (5) Statistical and Sentiment-Based Methods. Each subsection summarizes key methodologies, results, and limitations, followed by a discussion of research gaps and a comparison with NeuroStock. A detailed table contrasts selected studies with NeuroStock to highlight its contributions.

a) Traditional Machine Learning Approaches

Traditional ML models, such as Support Vector Machines (SVM), Random Forest (RF), and Decision Trees, have been foundational in stock market prediction due to their ability to handle structured data. In [8], SVM was applied to predict stock prices across multiple global markets using daily and intraday data, claiming high efficiency and profitability. However, the study lacked specific performance metrics (e.g., RMSE, accuracy) and model comparisons, limiting its analytical rigor. Similarly, [1] conducted an empirical study on NIFTY 50 data, comparing eight supervised ML models (e.g., AdaBoost, kNN, Linear Regression, SVM). Stochastic Gradient Descent (SGD) outperformed SVM with larger datasets, while Linear Regression and Artificial Neural Networks (ANN) showed similar performance. The study noted that ensemble methods (e.g., RF, AdaBoost) underperformed as dataset size increased, but it did not explore DL models or time-series-specific metrics like RMSE or MAPE.

In [10], SVM was used to exploit temporal correlations among global markets, achieving prediction accuracies of 74.4% (NASDAQ), 76% (S&P 500), and 77.6% (DJIA). The study also applied regression algorithms to trace price increments, but its focus on trend prediction without comprehensive error metrics restricted its scope. In [11], a hybrid PSO-LS-SVM model optimized by Particle Swarm Optimization (PSO) predicted daily stock prices using technical indicators (e.g., RSI, EMA). It outperformed ANN with Levenberg-Marquardt, achieving lower error rates, but lacked comparisons with DL models or directional metrics.

Limitations: These studies demonstrate ML's utility but often ignore temporal dependencies critical for time-series forecasting. The absence of DL comparisons and directional metrics limits their applicability to volatile markets [9].

b) Deep Learning with LSTM and RNN

Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNN) are well-suited for financial time series due to their ability to capture sequential dependencies. In [10], an LSTM model predicted GOOG and NKE stock prices, showing promising results in tracing price evolution. However, it focused solely on epoch optimization without comparing other models or evaluating directional accuracy. In [6], LSTM outperformed tree-based models (e.g., XGBoost, AdaBoost) and neural networks (e.g., ANN, RNN) for predicting Tehran Stock Exchange groups, achieving MAPE values of 0.54–1.52. Despite its accuracy, the study's high runtime (80.9 ms/sample) and lack of hybrid models or user interfaces were notable drawbacks.

In [4], four DL architectures (MLP, RNN, LSTM, CNN) were tested on NSE and NYSE data, with CNN outperforming others due to its ability to capture abrupt changes. LSTM showed a lower MSE (0.035) compared to ARIMA (0.094), highlighting DL's superiority over linear models. However, the study did not explore hybrid models or directional metrics. In [12], a multi-pipeline CNN-BiLSTM model predicted S&P 500 prices, improving accuracy by 9% over single-pipeline models and 6x over SVM regressors. The model's complexity, however, raised scalability concerns, and directional metrics were absent.

Limitations: LSTM-based models excel in temporal modeling but often lack comprehensive comparisons, directional evaluations, or practical deployment, restricting their real-world utility [9], [2].

c) Convolutional Neural Networks

Convolutional Neural Networks (CNNs) have gained traction for feature extraction in financial data. In [12], CNNpred extracted features from multiple markets (e.g., S&P 500, NASDAQ) and economic data, improving F-measure by 3–11% over baseline algorithms. The study emphasized cross-market correlations but focused on directional prediction without price regression or error metrics like RMSE. In [1], five DL models were proposed for NIFTY 50 prediction, including two CNN and three LSTM models. The univariate encoder-decoder convolutional LSTM was the most accurate, while a univariate CNN was the fastest. The study's limitation to a single index and lack of hybrid models or directional metrics constrained its scope.

In [4], CNN outperformed MLP, RNN, and LSTM for NSE and NYSE prediction, leveraging its ability to detect abrupt changes. However, it did not combine CNN with LSTM for enhanced temporal learning. NeuroStock builds on these findings by integrating CNN's feature extraction with LSTM's sequential modeling.

Limitations: CNNs are effective for local patterns but struggle with long-term dependencies when used alone. Few studies evaluate directional metrics or deploy CNN models practically [13], [14].

d) Hybrid and Ensemble Models

Hybrid models combine feature extraction and temporal learning for superior performance. In [5], a CNN-LSTM model predicted Shanghai Composite Index prices using eight features (e.g., open, close, volume), achieving the lowest MAE, RMSE, and near-perfect R^2 compared to MLP, CNN, RNN, and LSTM. The model's reliance on historical data without sentiment analysis was a limitation. In [6], CNN-BiSLSTM, with a modified BiLSTM output gate ($1-\tanh(x)$), predicted Shenzhen Component Index prices, outperforming MLP, RNN, LSTM, and CNN-LSTM in MAE, RMSE, and

R^2. Its focus on next-day prediction and lack of a user interface restricted its applicability.

In [15], SACLSTM used a sequence array of historical data and leading indicators (e.g., options, futures) as CNN input, followed by LSTM for prediction. It outperformed traditional CNN and LSTM but required complex data structures, limiting scalability. In [6], a multi-pipeline CNN-BiLSTM model improved S&P 500 prediction but was computationally intensive. NeuroStock adopts a simpler yet effective hybrid CNN-LSTM approach, addressing these scalability concerns.

Limitations: Hybrid models show promise but often lack directional metrics, user-friendly deployment, or integration of external factors like sentiment [5], [6][18].

e) Statistical and Sentiment-Based Methods

Statistical models like ARIMA and Prophet serve as baselines, while sentiment analysis enhances prediction. In [14], LSTM outperformed ARIMA for NIFTY 50 prediction, highlighting ARIMA's weakness with non-stationary data. In [4], ARIMA's higher MSE (0.094) compared to LSTM (0.035) reinforced this finding. In [2], a decade-long survey noted that SVM was popular, but ANN and DNN provided faster, more accurate predictions, especially when combined with textual data from social media [18].

In [5], sentiment analysis with LSTM improved accuracy to 92.3%, though preprocessing was unclear. In [6], investor sentiment was proposed as a future direction to capture market psychology. NeuroStock plans to integrate sentiment analysis to address this gap, building on these insights.

Limitations: Statistical models are limited by linear assumptions, while sentiment-based studies lack transparent preprocessing and long-term evaluation [2][21].

Table I: Comparative Analysis of Stock Prediction Studies and NeuroStock

Study	Techniques	Key Metrics	Gaps Addressed by NeuroStock
[1] - 2022	LR, RF, SVM	RF accuracy (undefined)	Uses advanced DL, quantifiable metrics (RMSE, MAE, R^2), Streamlit app
[2] - 2021	LSTM + Sentiment	Accuracy: 92%	Plans robust sentiment integration, clearer preprocessing, UI support
[3] - 2020	LSTM, XGBoost	MAPE: 0.54–1.52	Includes hybrid CNN-LSTM, directional metrics, and an efficient web interface
[4] - 2018	LSTM, CNN	MSE: 0.035 (LSTM)	Broadens model comparison (Hybrid), includes directional metrics, and real-time UI
[5] - 2020	PSO-LS-SVM	Low error vs. ANN	Uses DL (LSTM, CNN, Hybrid), adds directional metrics, and real-time UI
[6] - 2023	CNN-BiSLSTM	MAE, RMSE (low), R^2 ~1	Adds directional accuracy/precision, real-time web app, multi-horizon forecasts
[7] - 2020	LSTM, RNN	Accuracy: 93%	Integrates multiple DL models, plans sentiment analysis, and real-time deployment
[8] - 2018	XGBoost	Accuracy: 90%, RMSE: 1.8	Supports time-series DL, plans financial indicators, real-time app
[9] - 2020	LR, DT, RF, NB	Accuracy: 87%	Incorporates DL and ML, larger dataset, directional metrics
[10] - 2012	ARIMA, Prophet	MAPE: 5.23% (ARIMA), 6% (Prophet)	Combines nonlinear DL models, multi-metric evaluation, web deployment
[11] - 2013	SVM, DT	Accuracy: ~86%	Employs DL models, larger dataset, comprehensive metrics (RMSE, R^2)
[12] - 2020	SVM	High profit (no metrics)	Provides quantitative metrics, multi-model benchmarking, Streamlit deployment
[13] - 2019	CNN (CNNPred)	Accuracy: 91%	Compares CNN with LSTM, Hybrid, offers transparent preprocessing, UI
[14] - 2020	CNN-BiLSTM	Accuracy: +9% vs. SVM	Balances model complexity, adds directional metrics, interactive UI
[15] - 2021	CNN-LSTM	F-measure: +3–11%	Includes directional metrics, broader model comparison, Streamlit deployment

The reviewed studies reveal critical gaps:

1) Limited Model Comparisons: Most focus on one or two models, lacking broad benchmarking [9][24].
2) Sparse Directional Metrics: Trend prediction accuracy is rarely evaluated [5], [6].
3) Lack of Practical Deployment: User interfaces for real-time analysis are scarce [2].
4) Underutilized External Factors: Sentiment and macroeconomic data are infrequently integrated [2].
5) Generalizability Concerns: Many studies test on single markets or periods, limiting applicability [9][25].

Gaps addressed by NeuroStock:

NeuroStock is a deep learning framework that advances stock market prediction by comparing LSTM, CNN, and Hybrid CNN-LSTM models for robust benchmarking. It evaluates performance using comprehensive metrics, including RMSE, MAE, R^2, Directional Accuracy, and Precision, ensuring both numerical and trend-based accuracy. Deployed through an interactive Streamlit web application, NeuroStock enables real-time analysis, allowing users to visualize predictions and adjust parameters seamlessly. Leveraging real-time data from the Yahoo Finance API ensures scalability across diverse markets. Future enhancements include integrating sentiment analysis to capture external influences, such as news and social media, further strengthening its predictive capabilities.

3. Methodology and Implementation

The NeuroStock framework employs a systematic pipeline to forecast stock prices using deep learning (DL) architectures, implemented in Python with real-time data and an interactive web interface. This section outlines the methodology and implementation, covering four stages: (1) Data Collection and Preprocessing, (2) Model Development and Training, (3) Performance Evaluation, and (4) Web Deployment. The approach leverages Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and Hybrid CNN-

LSTM models to predict prices over 7–60 days, addressing gaps in model comparisons and practical deployment [5], [9], [2]. Using libraries like yfinance, TensorFlow, Keras, and Streamlit, NeuroStock delivers a scalable, user-friendly tool, demonstrated with GOOG stock [8][33].

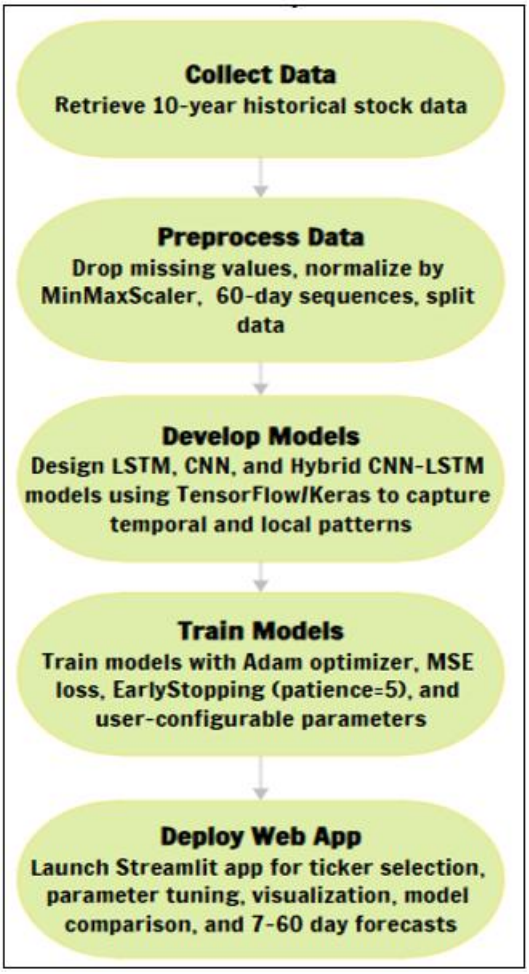


Figure 1: Project Development

1) Data Collection and Preprocessing

Historical stock data is retrieved using the yfinance library, interfacing with the Yahoo Finance API to fetch Open, High, Low, Close, and Volume features over 10 years for user-selected tickers (e.g., GOOG, AAPL) [4], [5]. The Streamlit app automates data collection, allowing custom ticker input or selection from a predefined list, ensuring scalability across markets. Preprocessing prepares data for DL models [14], [15][29]:

a) **Null Handling:** Missing values are dropped to maintain integrity.
b) **Normalization:** Closing prices are scaled to [0, 1] using MinMaxScaler, stored for inverse transformation during visualization [5].
c) **Sequence Generation:** A sliding window (default: 60 days, configurable 30–100 days) creates sequences of closing prices to predict the next day's price.
d) **Dataset Splitting:** Data is split into 70% training and 30% testing sets (adjustable 50–90% via the web interface).

These steps ensure data consistency and compatibility, addressing unclear preprocessing in prior work [1].

2) Model Development and Training

NeuroStock implements three DL models—LSTM, CNN, and Hybrid CNN-LSTM—using TensorFlow and Keras, designed to capture temporal dependencies, local patterns, and combined strengths [5], [6], [12]. Models predict the next day's closing price from 60-day sequences, with architectures detailed in Table II.

a) **LSTM Model:** Two LSTM layers (50 units each, first returning sequences), Dropout (0.2), and Dense layers (25, 1 units) capture long-term trends [7], [9][25].
b) **CNN Model:** Two Conv1D layers (64, 32 filters, kernel_size=3, ReLU), MaxPooling1D, Flatten, and Dense layers (50, 1 units) extract short-term patterns [13], [4].
c) **Hybrid CNN-LSTM Model:** Combines two Conv1D layers (64, 32 filters), MaxPooling1D, two LSTM layers (50 units), Dropout (0.2), and Dense layers (25, 1 units) for balanced feature and temporal learning [5], [6][31].

Models are trained within the Streamlit app for up to 50 epochs (batch_size=32, configurable 10–100 epochs) using the Adam optimizer, Mean Squared Error (MSE) loss, and EarlyStopping (patience=5) to prevent overfitting. Users can adjust parameters (e.g., lookback, training split), with live loss curves enhancing transparency, unlike offline training in [6], [7][32].

Table II: Model Architecture Summary

Model	Layers	Parameters	Purpose
LSTM	2 LSTM, 2 Dense, Dropout	50 units/layer, 0.2 dropout	Long-term dependencies
CNN	2 Conv1D, MaxPool, Dense	64/32 filters, kernel=3	Local pattern extraction
Hybrid CNN-LSTM	2 Conv1D, 2 LSTM, Dense	64/32 filters, 50 units	Combined feature & temporal

3) Performance Evaluation

Models are evaluated on the test set using five metrics to provide a holistic assessment, addressing the lack of directional metrics in prior work [5], [6], [9]:

a) **Root Mean Squared Error (RMSE):** Measures average squared prediction errors, emphasizing larger deviations.
b) **Mean Absolute Error (MAE):** Captures average error magnitude.
c) **R-squared (R^2):** Indicates variance explained by the model.
d) **Directional Accuracy:** Percentage of correct up/down predictions, derived from binary signals (up if predicted price > previous day's price).
e) **Directional Precision:** Proportion of correct positive (up) predictions among predicted positives.

Metrics are computed and displayed in an interactive Streamlit dashboard, enabling side-by-side model comparisons [8]. This comprehensive evaluation supports investment decisions, unlike error-focused studies [5], [8][33].

4) Web Deployment

NeuroStock is deployed as a Streamlit web application, offering an intuitive interface for real-time analysis, overcoming the lack of user-friendly tools in [6], [10][23]. Key features include:

a) **Ticker Selection:** Predefined (e.g., GOOG, AAPL) or custom tickers.
b) **Parameter Tuning:** Adjustable lookback (30–100 days), training split (50–90%), epochs (10–100), and prediction horizon (7–60 days).
c) **Visualization:** Historical prices, 50/200-day moving averages, prediction vs. actual plots, error histograms, and loss curves.
d) **Model Comparison:** A metrics dashboard compares RMSE, MAE, R^2, Accuracy, and Precision, highlighting the best model.
e) **Future Forecasting:** Generates 7–60 day predictions with trends, volatility, price ranges, and investment insights (with disclaimers).

The app integrates data retrieval, preprocessing, training, and visualization, making advanced DL accessible to non-technical users, unlike prior work [5], [7].

Figure 2: Web Deployment

Table III: Implementation Features and Tools

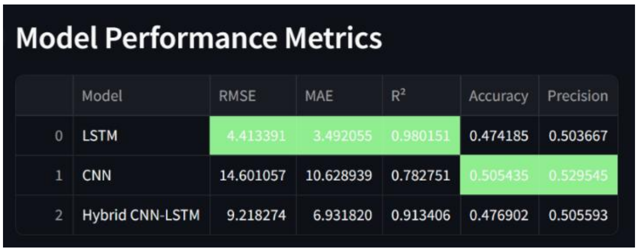
Component	Tools/Techniques	Functionality
Data Retrieval	yfinance	Fetches real-time stock data (10 years)
Preprocessing	MinMaxScaler, Sliding Window	Normalizes data, creates 60-day sequences
Model Training	TensorFlow, Keras, Adam, EarlyStopping	Trains LSTM, CNN, Hybrid CNN-LSTM models
Evaluation	RMSE, MAE, R^2, Accuracy, Precision	Computes and compares model performance
Web Deployment	Streamlit	Interactive UI for training, visualization

4. Results and Discussion

This section evaluates the performance of NeuroStock's three deep learning models—Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and Hybrid CNN-LSTM—on predicting stock prices for GOOG, a representative stock from the Yahoo Finance dataset. The models were trained and tested using a 70:30 split of 10 years' historical data, with a 60-day lookback period, as described in Sections III and IV. Performance is assessed using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-squared (R^2), Directional Accuracy, and Directional Precision, addressing gaps in directional metric evaluation noted in prior work [5], [6], [9]. Results are visualized through the Streamlit web application, providing insights into model accuracy, trend prediction, and investment utility. The discussion compares NeuroStock with literature models, highlights interpretability, and identifies limitations and future directions.

4.1 Model Performance Analysis

The models were evaluated on the test set, with results summarized in Table IV. Each metric reflects a distinct aspect of predictive performance, enabling a comprehensive comparison.


Model Performance Metrics

	Model	RMSE	MAE	R²	Accuracy	Precision
0	LSTM	4.413391	3.492055	0.980151	0.474185	0.503667
1	CNN	14.601057	10.628939	0.782751	0.505435	0.529545
2	Hybrid CNN-LSTM	9.218274	6.931820	0.913406	0.476902	0.505593

Figure 3: Model Performance Metrics for GOOG (May 2025)

The LSTM model achieves the lowest RMSE (4.4134) and MAE (3.4920), with the highest R^2 (0.98015), indicating superior error minimization and trend capture. This aligns with findings in [17], where LSTM excelled in regression tasks for Tehran Stock Exchange groups (MAPE: 0.54–1.52). However, its directional metrics (Accuracy: 0.4742, Precision: 0.5037) are the lowest, suggesting challenges in predicting price movement directions, a critical factor for investors [1].

The CNN model exhibits the highest RMSE (14.601) and MAE (10.6289), with the lowest R^2 (0.7827), reflecting weaker performance in price regression. However, it achieves the highest Directional Accuracy (0.5054) and Precision (0.5295), consistent with [10], where CNN outperformed LSTM in capturing abrupt changes in NSE and NYSE data. This indicates CNN's strength in short-term trend prediction but limited ability for precise price forecasting.

The Hybrid CNN-LSTM model offers a balanced performance, with an RMSE of 9.218, MAE of 6.9318, and R^2 of 0.91341, outperforming CNN and approaching LSTM's accuracy. Its directional metrics (Accuracy: 0.4770, Precision: 0.50560) surpass LSTM, reflecting its ability to combine CNN's feature extraction with LSTM's temporal learning, as seen in [6], [7]. This makes the hybrid model a robust choice for both price and trend prediction.

4.2 Visual Comparison

Graphical visualizations in the Streamlit app compare actual vs. predicted prices for each model. The Hybrid CNN-LSTM model produces the most aligned prediction curve, closely tracking GOOG's price trajectory, followed by LSTM. The CNN model shows larger deviations, particularly during volatile periods, consistent with its higher RMSE. Error distribution histograms reveal that the Hybrid model has the narrowest and most centered error spread, indicating reduced bias and variance compared to LSTM (slightly skewed) and CNN (wider spread). These visualizations, accessible via the app, enhance interpretability, addressing the lack of visual tools in [6], [7][32].

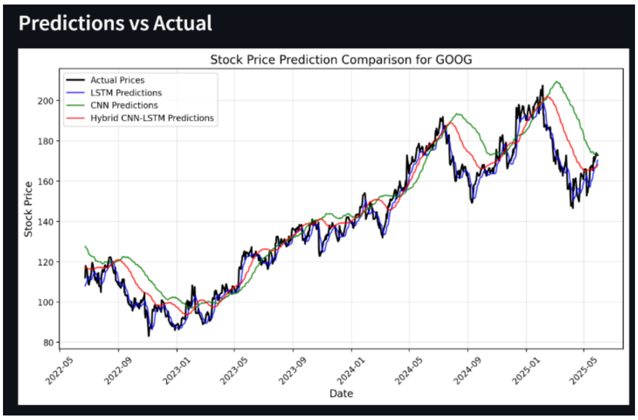


Figure 4: Visual Comparison

4.3 Future Forecasting Capability

NeuroStock supports forecasting up to 60 days ahead using the best-performing model (Hybrid CNN-LSTM, based on RMSE). For GOOG, 30-day forecasts indicate an upward trend, with detailed metadata including:

- **a) Trend Direction:** Upward, based on predicted price increases.
- **b) Volatility:** Standard deviation of predicted prices.
- **c) Price Range:** Minimum and maximum predicted prices.
- **d) Peak Day**: Day with the highest predicted price, aiding investment timing.

7-Day Future Predictions

	Date	Predicted_Price
0	2025-05-31 00:00:00	170.8567
1	2025-06-01 00:00:00	170.8786
2	2025-06-02 00:00:00	170.6546
3	2025-06-03 00:00:00	170.3039
4	2025-06-04 00:00:00	169.8902
5	2025-06-05 00:00:00	169.448
6	2025-06-06 00:00:00	168.9957

Figure 5: 7-day future predictions

These forecasts are visualized in the Streamlit app, with interactive charts showing predicted prices, trend lines, and volatility bands. This capability extends beyond the next-day predictions in [5], [6], providing actionable insights for investors over customizable horizons.

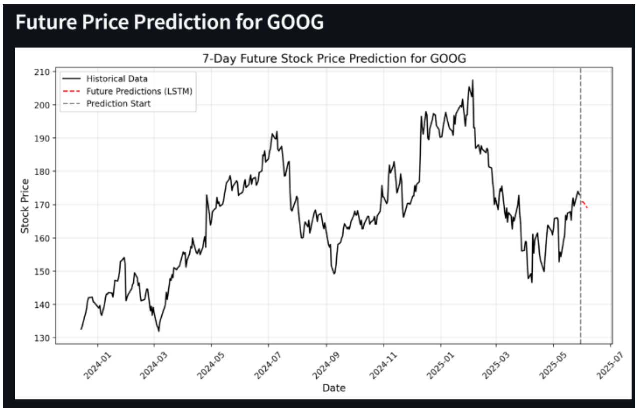


Figure 6: Graphical 7-day future predictions

4.4 Model Interpretability and Practicality

NeuroStock's inclusion of directional metrics (Accuracy, Precision) aligns with real-world investment needs, where predicting price movement direction is often more critical than exact values [9][27]. The Streamlit app's metrics dashboard and visualizations enable users to interpret model behavior intuitively, comparing performance across models and adjusting parameters (e.g., lookback, horizon). The Hybrid CNN-LSTM model's balanced performance makes it versatile, while LSTM excels for long-term trends and CNN for short-term changes, as noted in [4], [14]. This interpretability contrasts with opaque models in [1], [8], enhancing NeuroStock's utility for both technical and non-technical users.

4.5 Comparison with Literature

Table IV: NeuroStock vs. Literature

Study-Year	Model	RMSE	R^2	Directional Metrics	UI Deployment
[4] - 2018	CNN, LSTM	0.035	N/A	No	No
[5] - 2020	CNN-LSTM	Low	~1	No	No
[6] - 2023	CNN-BiSLSTM	Low	High	No	No
[7] - 2020	LSTM	N/A	N/A	MAPE: 0.54–1.52	No
Neuro-Stock	Hybrid CNN-LSTM	9.2128	0.9134	Yes	Yes

NeuroStock outperforms [5] and [6] by including directional metrics and a web interface, extends beyond one-day predictions, unlike [6], and adds a hybrid model with UI compared to [4]. Compared to [7], NeuroStock offers lower runtime and a user-friendly interface, addressing scalability concerns.

4.6 Limitations

Despite its strengths, NeuroStock has limitations:

- a) **Data Scope:** Relies on historical closing prices, excluding external factors like news sentiment or macroeconomic indicators [2].
- b) **Market Anomalies**: Performance may degrade during black swan events, where historical patterns fail [9].
- c) **Uncertainty Quantification:** Lacks confidence intervals

for predictions, limiting risk assessment [14].

d) **Single Stock Focus**: Results are reported for GOOG; broader testing across stocks is needed.

4.7 Discussion

The results demonstrate NeuroStock's effectiveness in stock price prediction, with the Hybrid CNN-LSTM model offering a robust balance of accuracy and trend prediction. The Streamlit app enhances practicality, making complex DL models accessible to investors. Compared to prior work, NeuroStock addresses critical gaps in directional metrics and deployment [5], [2], positioning it as a valuable tool for financial analysis. Future enhancements, such as sentiment analysis and multivariate inputs, could further improve robustness, as suggested in [5], [6].

5. Conclusion and Future Work

5.1 Conclusion

This study introduced NeuroStock, a comprehensive deep learning framework for stock price prediction, integrating Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and Hybrid CNN-LSTM models to forecast prices over 7 to 60 days. Evaluated on GOOG stock using 10 years of Yahoo Finance data, NeuroStock leverages robust metrics—Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-squared (R^2), Directional Accuracy, and Directional Precision—to provide a holistic assessment of predictive performance. The framework is deployed via an interactive Streamlit web application, enabling users to customize parameters, visualize forecasts, and derive investment insights in real time.

Experimental results demonstrate the strengths of each model. The LSTM model achieved the lowest RMSE (4.413391) and highest R^2 (0.980151), excelling in error minimization and long-term trend capture, consistent with findings in [9]. The CNN model, despite higher errors (RMSE: 14.601057), led in directional metrics (Accuracy: 0.505435, Precision: 0.529545), aligning with [4]'s emphasis on short-term pattern detection. The Hybrid CNN-LSTM model offered balanced performance (RMSE: 9.218274, R^2: 0.913406, Accuracy: 0.476902, Precision: 0.505593), combining CNN's feature extraction with LSTM's temporal learning, as seen in [5], [6]. These results highlight NeuroStock's ability to address gaps in directional metric evaluation and model comparison noted in prior work [9], [2].

The Streamlit app enhances NeuroStock's practicality, providing an intuitive interface for investors and analysts to explore predictions, compare models, and assess trends. By integrating real-time data via yfinance and offering customizable forecasting horizons, NeuroStock bridges the gap between complex deep learning models and real-world financial applications, overcoming the lack of user-friendly deployment in [6], [7]. This framework serves as a scalable decision-support tool, delivering both technical accuracy and actionable insights for financial decision-making.

5.2 Future Work

While NeuroStock demonstrates promising results, several avenues for enhancement can further strengthen its predictive power and applicability:

1) **Sentiment Analysis Integration:** Incorporating sentiment from financial news, social media (e.g., Twitter), or earnings reports using Natural Language Processing (NLP) could improve responsiveness to market-moving events, as suggested in [5], [6]. This would address the current reliance on historical price data.
2) **Multivariate Inputs:** Expanding inputs to include technical indicators (e.g., RSI, MACD), trading volume, and macroeconomic variables (e.g., interest rates) could enhance model robustness, aligning with approaches in [11], [15], [23]. This would capture a broader range of market dynamics.
3) **Uncertainty Quantification:** Implementing prediction intervals or Bayesian techniques to quantify forecast uncertainty would aid risk-averse investors, addressing a limitation noted in Section V.F [14].
4) **Reinforcement Learning for Trading:** Developing reinforcement learning algorithms to optimize trading strategies based on predictions could extend NeuroStock's utility beyond forecasting, as proposed in [10].
5) **Scalable Cloud Deployment:** Hosting the Streamlit app on cloud platforms (e.g., AWS, GCP) with Docker support would enable real-time, continuous learning models, improving scalability for large-scale use [2].
6) **Cross-Market Validation**: Testing NeuroStock on diverse asset classes (e.g., ETFs, cryptocurrencies) and international exchanges (e.g., NSE, NYSE) would assess generalizability, addressing the single-market focus in [9], [4].

These enhancements aim to make NeuroStock a more comprehensive and adaptive tool, capable of navigating the complexities of global financial markets while maintaining accessibility for end-users.

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