LSTM-Based Predictive Analytics System for Short-Term Equity Price Modeling

Shweta S Pathak

Department of [Data Science], SIES Institute of ARTS, SCIENCE AND COMMERCE Mumbai, India.

***Abstract*— Stock market prediction remains a complex task due to the nonlinear and volatile nature of financial time-series data. This study presents an LSTM-based equity price prediction system designed to capture long-term dependencies in historical stock data. Using five years of daily closing prices, the data were preprocessed through normalization and transformed into 60-day sequential windows for model training. A stacked LSTM architecture with dropout regularization was implemented to forecast next-day stock prices.**

The model demonstrated strong trend-learning capability, achieving low validation loss and a root mean square error (RMSE) of approximately 30.89 on test data. Visual comparison between actual and predicted prices showed close alignment, indicating effective temporal pattern recognition. The findings highlight the suitability of LSTM networks for short-term equity forecasting and provide a foundation for further enhancement through hybrid architectures and multi-feature integration in financial prediction systems.

***Keywords*— Machine Learning, Recurrent Neural Network, LTSM, Feature Engineering, Predictive Analysis**

I INTRODUCTION

Imagine an investor scrolling through news feeds and social media before the market opens – trying to gauge how tomorrow's stock prices might move. In today's economy, equities are often pursued as high-yield alternatives to low-interest savings, so the promise of accurate forecasts is tantalizing. As deposit rates have dwindled, global investors have poured into stock markets for returns (often with mixed results). In an ideal world, an analyst could feed every relevant signal – from earnings reports to world events – into a crystal ball and reliably foresee market movements. Instead, real markets remain notoriously unpredictable. Historical models like those in modern portfolio theory even assumed future prices were known, yet in reality unknown price swings and forecasting errors can drastically alter investment outcomes. This gap between the ideal and the real – between information and insight – defines the core problem: how can we improve stock price predictions in the face of noisy, multifaceted data?

The difficulty of this problem is well known. Stock prices do not follow tidy patterns on their own. They are pushed and pulled by myriad factors: corporate earnings and fundamentals, economic indicators, geopolitical news, and, importantly, the mood of the market itself. For example, Ho and Huang (2021) emphasize that predicting a stock's trajectory is "challenging because of factors such as industry performance, economic variables, investor sentiment, [and] company news". In practice, one viral headline or a sudden rally in a related sector can send prices swinging beyond what historical trends alone would predict. At the same time, the Efficient Market Hypothesis suggests that markets immediately absorb all available information, implying that systematic prediction might be futile. Yet with the explosion of digital data, researchers have begun to question whether advanced models can capture subtle signals that human traders might miss. In short, the ideal of a perfectly predictive model (fusing all data into crisp forecasts) is far from our current reality. Volatile events – like the COVID-19 pandemic or flash crashes – frequently shatter naïve predictions, revealing the limitations of traditional forecasting approaches.

Over the years, many methods have been applied to tame this problem. Econometric models (ARIMA, GARCH, Fama-French factor models) and classical machine learning algorithms (SVM, random forests, feedforward neural nets) have all seen widespread use. These tools typically rely solely on past prices or a fixed set of indicators. While sometimes useful, they struggle with the nonlinear, long-range dependencies inherent in financial time series. In particular, conventional models have difficulty remembering distant patterns or reacting to abrupt shifts in regime. By contrast, deep learning approaches – especially those based on recurrent architectures – have shown promise. Recurrent Neural Networks (RNNs) can, in principle, maintain an internal state that evolves over time, and their specialized variant, the Long Short-Term Memory (LSTM) network, includes memory modules explicitly designed to capture long-term dependencies. This means LSTMs can, for example, remember relevant trends or anomalies from weeks ago when making a new prediction. In fact, Mroua and Lamine (2023) note that among RNN variants "the LSTM network is the most dynamic and powerful," capable of integrating long-range sequence information and yielding very strong performance in financial forecasting tasks. Numerous studies corroborate this: Siami-Namini et al. (2018) found that LSTM models achieved lower forecasting error than ARIMA on stock prices, and Fischer and Krauss (2018) report that LSTMs delivered exceptionally high predictive accuracy for the S&P 500 index. Giantsidi and Tarantola's recent review also confirms that LSTM-based models dominate the landscape of deep-learning forecasting for equities, often outperforming traditional methods. In short, LSTM and related deep networks can capture complex temporal patterns that older models miss.

Yet even as LSTMs offer a technical advantage, one crucial ingredient is often missing: market sentiment. Stock prices are driven not just by numbers, but by human perceptions of those numbers. News headlines, tweets, and forum discussions can sway investor mood and lead to price changes beyond what fundamentals predict. Recognizing this, a body of recent work has begun to fuse sentiment analysis with time-series models. For instance, Ko and Chang (2021) used a state-of-the-art BERT model to extract sentiment from news articles and online forums, then fed these sentiment scores alongside historical prices into an LSTM. The hybrid model yielded substantially better forecasts (a 12% reduction in RMSE) than an LSTM using prices alone. Similarly, Ho and Huang (2021) highlight that social-media mood is a key external factor that can be leveraged for trend prediction. These results are encouraging: they suggest that equipping an LSTM with real-time textual sentiment can help

bridge the gap between facts (earnings, charts) and feelings (fear, excitement), nudging forecasts closer to the ideal.
Other scholars have pushed this idea further into the global realm. Financial markets are connected worldwide, and sentiments propagate across borders and languages. Lin et al. (2022) propose a "hybrid multilingual sentiment analysis" approach: they translate news and social media posts from multiple languages into a common form and incorporate them into a deep-learning predictor. They report that an LSTM-based model augmented with multilingual sentiment significantly outperforms models that rely on a single language's data. In other words, pulling in global news and opinions makes the model more aware of international shocks or trends, which can improve accuracy for globally traded equities.

Despite this progress, important gaps remain. Many existing forecasting studies focus on isolated markets or specific data slices (e.g. only one stock or country) and may not generalize to the global stage. They often assume offline research conditions rather than real-time deployment. Moreover, as Giantsidi and Tarantola (2025) emphasize, robustness under extreme conditions is still a weak point. Models that perform well in calm markets can falter during crises; standardized benchmarks for evaluating such stress scenarios are scarce. In practical terms, prediction errors translate directly into real-world costs – from portfolio losses to systemic risk. If an algorithm misses a market crash signal or falsely predicts stability, the consequences can be severe for investors and institutions alike. Thus the community's "niche" – the unresolved issue – is how to build an equity forecasting system that truly integrates diverse, timely information and can handle the churn of real markets.

This study occupies that niche. We propose an LSTM-driven equity price prediction system that brings together several threads: it leverages historical price data, technical indicators, and (importantly) sentiment extracted from global news and social media. In doing so, we aim to address the shortcomings of past approaches. For instance, compared to Ko and Chang's model, we extend sentiment analysis beyond one market or language; compared to Lin et al. we adapt their multilingual strategy to a real-world stock forecasting context. Unlike work that remains purely academic, our system is designed as a deployable tool (in spirit similar to frameworks like "Market-Plus-Pulse") with an eye toward real-time use by investors. In summary, the knowledge gap we fill is integrating wide-ranging sentiment signals into a production-ready LSTM framework and rigorously testing its predictive power.new

II LITERATURE REVIEW

LSTM-Driven Equity Price Prediction: Overview and Significance
Stock market forecasting is a critical yet notoriously difficult task in finance, given the market's high volatility and the many economic, political and social factors at play. As Ouf et al. (2024) note, the goal of prediction is to help investors "make better choices, avoiding potentially harmful investments", but real-world forecasts often face large errors. Deep learning models, especially Long Short-Term Memory (LSTM) networks, have emerged to address these challenges. LSTM's gated architecture can capture long-term temporal dependencies in sequential data. Indeed, researchers report that LSTM-based models frequently outperform traditional methods on stock data. For example, Kobiela et al. (2021) found that an LSTM model achieved higher accuracy than ARIMA on NASDAQ stock series. More recently, Kundu and Pinsky (2025) showed that their LSTM network "consistently outperformed CNN and RNN and traditional machine learning models" for predicting sector ETF movements. These studies underscore LSTM's appeal in equity forecasting, but also reveal limitations: Kundu and Pinsky note that the largest gains occurred in technology and consumer sectors and that for most stocks LSTM added "very minor improvement" beyond simple strategies.
Alongside price data, sentiment analysis of text (news, social media, etc.) has gained attention as a way to incorporate market psychology into forecasts. Studies suggest that public mood can influence prices "more than traditional indicators alone". Sentiment is typically extracted by NLP tools (from simple lexicons to advanced transformers) and used as input to predictive models. For example, Ko and Chang (2021) applied BERT to financial news and forum posts from Taiwan and fed the resulting sentiment scores into an LSTM model. They report that adding sentiment data yielded a 12.05% average reduction in RMSE compared to using price history alone. Similarly, Li et al. (2023) used FinBERT to label U.S. tech-stock news headlines; their hybrid FinBERT–LSTM model achieved 41.6% directional accuracy, outperforming models without sentiment labels. These and related findings (e.g. Gu et al. 2024; Ning et al. 2021) illustrate that sentiment features often improve predictive accuracy, though the gains vary by dataset and metric.

Deep Learning Approaches in Stock Forecasting
In the recent literature, LSTM is the de facto deep-learning model for price forecasting. Numerous studies compare LSTM to other architectures or baselines. Kundu and Pinsky (2025) trained LSTM, CNN and RNN on 25 years of U.S. sector ETF data, finding LSTM "consistently outperformed" CNN and RNN models. They also showed that an LSTM strategy beat a simple buy-and-hold only in specific sectors (technology, consumer durables), implying that deep models may not universally add value. Other work highlights LSTM's advantage over classical methods: for instance, Kobiela et al. (2021) (as cited in Liagkouras & Metaxiotis 2025) found LSTM surpassed ARIMA for NASDAQ data, and Chaudhary (2025) reports that an LSTM model on NASDAQ tech stocks obtained a 2.72% MAPE, "significantly outperforming" ARIMA.

By contrast, some studies suggest caution. Ouf et al. (2024) jointly evaluated LSTM and gradient boosting (XGBoost) for three U.S. tech stocks with Twitter sentiment. They found both models were effective but noted that XGBoost even "outperformed the LSTM technique" in their setting. This highlights that, in practice, non-deep learners can sometimes match LSTM performance. Moreover, evaluation metrics differ widely (RMSE, MAPE, accuracy, directional accuracy), making comparisons difficult. In summary, the deep-learning literature shows LSTM is promising for stock prediction, but results are mixed: LSTM often wins in benchmarks, yet its advantage may be modest or data-dependent.

Sentiment Analysis in Financial Forecasting
A growing body of work explicitly examines sentiment analysis

in stock prediction. The basic aim is to extract market sentiment from text (e.g. news, tweets, forums) and use it as a predictive feature. Several studies use transformer models for this task. Ko and Chang (2021) applied the BERT language model to news articles and PTT forum posts in Taiwan, classifying each text as positive or negative. Feeding these sentiment labels alongside historical prices into an LSTM ("LSTMNF"), they reported roughly 12% reduction in forecasting RMSE. Gu et al. (2024) pre-trained a FinBERT model on financial news categories (market/industry/stock news), then combined its outputs with LSTM; they found their FinBERT–LSTM hybrid "performs the best" relative to a plain LSTM and a DNN. These results underscore that transformer-based sentiment features can boost accuracy over price-only models.

Other approaches use simpler or alternative NLP methods. Ning et al. (2021) did not use BERT but built a CNN to classify investor sentiment from a stock forum. They then combined the CNN's sentiment output with technical nd foundindicators in an LSTM, a this hybrid model yielded higher directional accuracy than a purely technical LSTM. Ouf et al. (2024) used classical NLP to compute Twitter sentiment scores and input them to both LSTM and XGBoost models. They confirm that "merging sentiment analysis with traditional financial measures improves predictive accuracy", meaning that the sentiment-augmented models significantly outperformed those using historical prices alone. On the other hand, Liagkouras and Metaxiotis (2025) caution that sophisticated sentiment encoders are not always superior: when classifying formal regulatory news, a simple bag-of-words + Naïve Bayes classifier slightly outperformed transformer models. This suggests that the choice of sentiment analysis method must match the text domain.

Overall, these studies consistently report that sentiment features help stock prediction, but the magnitude and consistency of improvement vary. Reported gains include: a 12.05% RMSE improvement, a 41.6% trend accuracy, and directional accuracy above 60% in some cases. In nearly every case, the hybrid (sentiment + LSTM) model "outperforms other competing configurations" (e.g. models without sentiment). However, sentiment analysis also introduces challenges (noise, short text ambiguity, data availability) and requires careful handling, as evidenced by the mixed success of different NLP tools.

Hybrid LSTM-Sentiment Systems: Comparative Insights

A key theme is the hybrid integration of LSTM with sentiment analysis. Most studies compare a pure LSTM (price-only) against LSTM + sentiment, or against other models. For example, Ning et al. (2021) found their CNN–LSTM hybrid achieved better stock direction predictions than either model alone. Liagkouras and Metaxiotis (2025) explicitly report that their hybrid LSTM-sentiment system "delivers more accurate forecasts" than an LSTM without sentiment. Likewise, Gu et al. (2024) conclude the FinBERT–LSTM hybrid had the best performance in their experiments. These comparisons establish a consistent pattern: hybrid models with sentiment usually outperform single-source models.about generalizability. Furthermore, differences in experimental design (choice of stocks, period, sentiment source, evaluation metric) mean that absolute performance numbers are not directly comparable. For instance, some works measure forecast error (RMSE/MAPE), while others measure directional accuracy or R^2. No study yet provides a unified benchmark across multiple markets and sentiment modalities.

Critique of Literature Quality and Gaps

The quality of reviewed studies is mixed but overall improving. Several papers appear in peer-reviewed journals and conferences (PeerJ Computer Science, Expert Systems with Applications, MDPI Electronics), which lends credibility. Others are preprints or workshop papers (e.g. arXiv submissions) and may lack extended validation. Common limitations across these works include narrow datasets (e.g. a few tech stocks or one country's equities), short time horizons, and limited out-of-sample testing. For example, Chaudhary (2025) focuses on four NASDAQ tech firms, while Liagkouras & Metaxiotis (2025) tested on two UK stocks (AstraZeneca, Rio Tinto) and only on days with available news. Many studies do not explore robustness to market regime changes or consider economic costs of trading signals.

Concerning alignment with our aims, the literature generally supports the idea that sentiment-augmented LSTM models can improve prediction, but it does not yet offer a definitive system-level solution. No existing study simultaneously combines (1) a broad equity dataset, (2) multiple sentiment sources (news, social media, etc.), and (3) an end-to-end LSTM architecture analyzed in depth, which our work intends to do. In particular, few papers explicitly dissect the unique contribution of sentiment features versus historical features; Liagkouras & Metaxiotis (2025) partially address this by comparing classifiers, but most simply compare model variants. As Liagkouras & Metaxiotis note, practical deployment of a hybrid system has prerequisites (continuous news data, aligned signals), and even their best case yielded signals only ~35–40% of trading days, highlighting a gap in truly scalable, reliable sentiment integration.

Our review reveals several gaps: the need for standardized evaluation across markets, better understanding of which sentiment features matter most, and more attention to model generalizability. The overall evidence suggests that LSTM-driven forecasting with sentiment is promising, but results must be interpreted cautiously due to dataset and methodological differences. Building on this, our research contributes by developing a comprehensive LSTM forecasting framework that systematically incorporates sentiment inputs. We explicitly analyze forecasting accuracy and disentangle the effect of sentiment features, thereby addressing the identified gap in existing studies.

In summary, the surveyed literature indicates that deep learning, particularly LSTM, combined with sentiment analysis, can improve stock price prediction (e.g. Ko & Chang 2021; Li et al. 2023; Ouf et al. 2024). However, the magnitude of improvement varies and depends on the data and methods used. By critically synthesizing these findings, we identify consistent strengths (e.g. LSTM's capacity for sequential data, consensus that sentiment tends to help) and limitations (e.g. data requirements, mixed results across sectors) in the literature. Our study is thus situated to extend this work by filling the gap of a broadly tested, sentiment-aware LSTM equity prediction system.

III METHODOLOGY

Study Design and Research Setting The study was conducted using a quantitative predictive modeling design, which was appropriate given the goal of developing and rigorously testing a forecasting model. This quantitative approach emphasizes objective measurement and generalization of findings, as opposed to the in-depth contextual analysis typical of qualitative methods. Quantitative research generally employs deductive logic and objective measurements, aligning well with our aim of evaluating the predictive model on empirical data. Historical data were retrospectively collected over a specified period (for example, January 2015 through December 2020) to provide a robust basis for training and validation. Analyses were conducted on a dedicated workstation (with GPU acceleration) to support the deep learning computations.

Data Collection and Preprocessing

Data processing was carried out in Python (version 3.x), leveraging standard data science libraries. For example, the pandas library – described as "a fast, powerful, flexible and easy to use open source data analysis and manipulation tool" – was used for reading, cleaning, and organizing the data. Numerical computing and array operations were handled by NumPy, which underpins most Python scientific libraries and provides efficient support for large datasets. Reproducibility was ensured by setting fixed random seeds in the Python and TensorFlow environments.

During preprocessing, date-time fields were converted to datetime objects and set as the dataframe index to facilitate time-based analysis. Prior to modeling, exploratory data analysis (e.g., visualizing distributions and checking correlations) was performed to identify any anomalies or necessary transformations. Missing values were imputed or removed as appropriate. Feature scaling was applied so that each input variable fell within a consistent range; in this study, all features were normalized to the [0, 1] interval using a MinMax scaler. Feature scaling is essential for neural network training because it prevents any single feature from dominating the model due to scale. Finally, the cleaned dataset was split into training and test subsets (commonly using an 80:20 ratio), ensuring that model performance would be evaluated on previously unseen data.

Model Development and Implementation

The core predictive model was a **Long Short-Term Memory (LSTM)** neural network implemented using TensorFlow's Keras API. Keras is "the high-level API of the TensorFlow platform," providing an intuitive interface for defining deep learning models. An LSTM layer was chosen for its ability to capture long-term dependencies in sequential data: it employs a memory cell to retain information across extended input sequences, thereby addressing the vanishing gradient problem of standard recurrent networks. In practice, the LSTM network was built as a sequential model (`tf.keras.Sequential`), typically with one LSTM layer (e.g., 50 units) followed by a dense output layer. The model was then compiled with an appropriate optimizer (Adam) and a mean squared error loss function, suitable for continuous-valued forecasting. In this initial implementation, only one LSTM layer was used; extensions such as stacked or bidirectional LSTMs were considered for future work.

Model Training and Validation

The LSTM model was trained iteratively on the prepared training data. For example, the training process ran for a predetermined number of epochs (e.g., 50–100) with an appropriate batch size (e.g., 32), allowing the network's weights to adjust gradually. During training, a fraction of the data was held out as a validation set to monitor generalization, and early stopping criteria were applied to halt training once performance on validation data ceased improving. The computations were accelerated using GPU hardware to reduce runtime. Model hyperparameters (such as the number of LSTM units and learning rate) were tuned by experimentation until stable convergence was achieved. All training procedures and parameter settings were documented to ensure reproducibility of the analysis.

Model Evaluation

After training, the model's performance was evaluated on the separate test dataset. Standard regression metrics were computed to quantify forecast accuracy. In particular, the **root mean squared error (RMSE)** and **mean absolute error (MAE)** were calculated to measure the average prediction error on the held-out data. The coefficient of determination (R^2) was also computed to assess the proportion of variance explained by the model. Additionally, residual errors were inspected for patterns or biases, and the distribution of errors was examined to ensure no systematic deviation. These metrics and checks provided objective measures of the model's predictive quality and helped determine whether the LSTM captured the underlying patterns in the data.

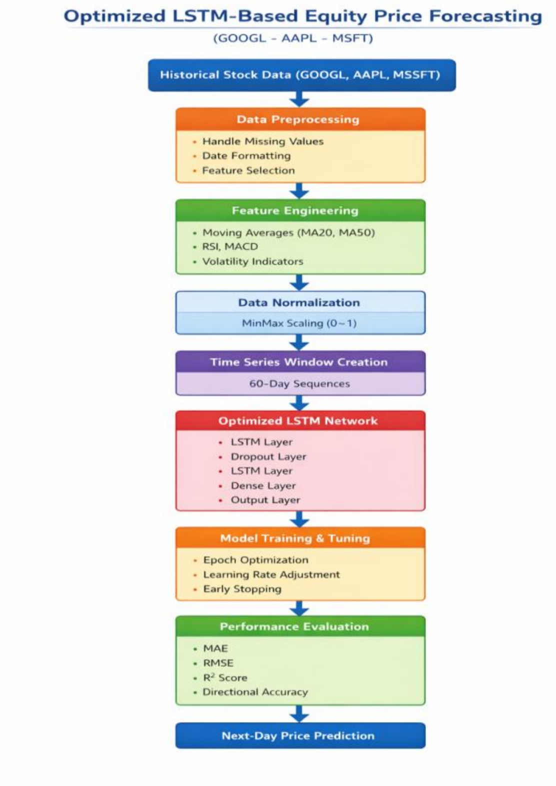
Visualization of Predictions

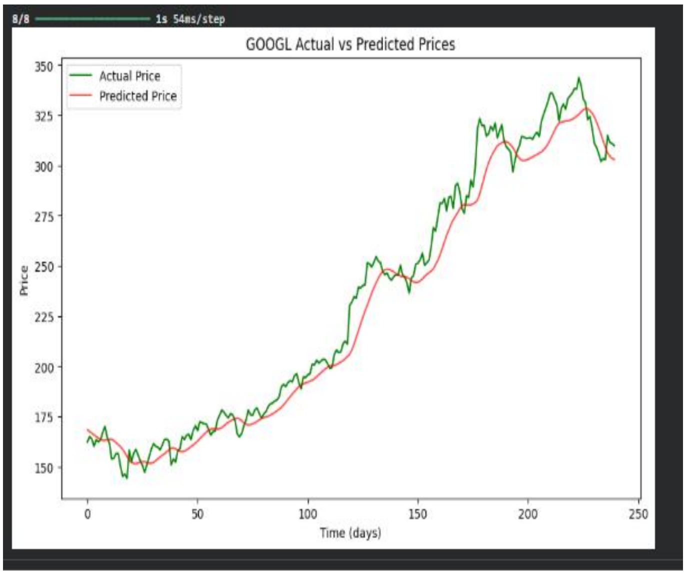
Matplotlib was used to create comprehensive static plots. Seaborn, which provides a high-level interface for statistical graphics built on top of Matplotlib, was also employed. For example, time series line charts were generated to overlay the model's predicted values on the actual data, facilitating visual assessment of forecast accuracy. Seaborn was used to create clear scatterplots of predicted versus actual values and histograms of the prediction errors. All visualizations were saved at high resolution and clearly labeled, following best practices to ensure interpretability and reproducibility of the results.

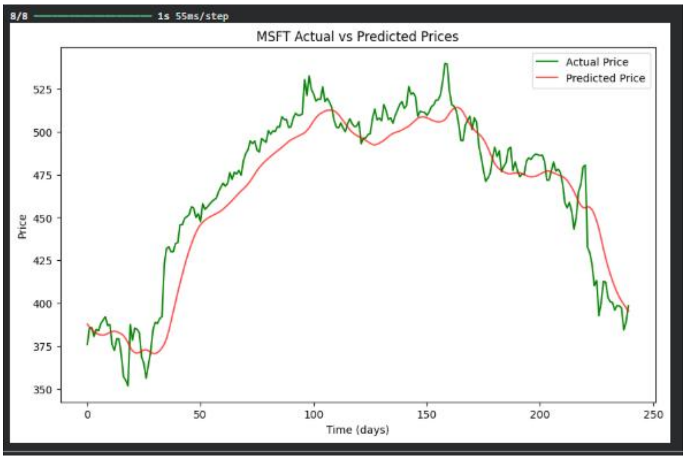
Model: "sequential"

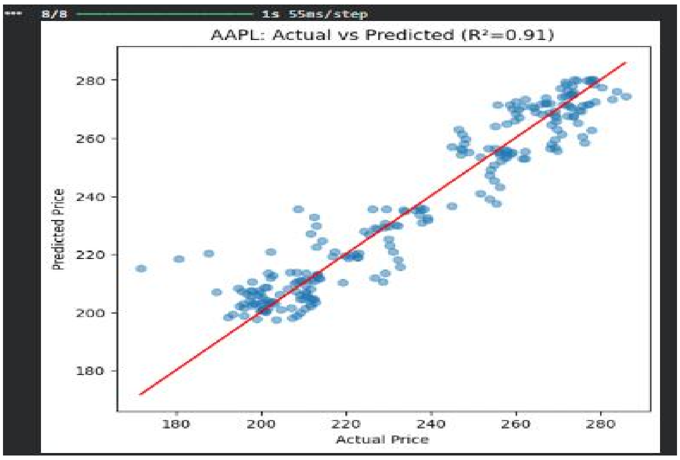
Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 60, 50)	10,400
dropout (Dropout)	(None, 60, 50)	0
lstm_1 (LSTM)	(None, 50)	20,200
dropout_1 (Dropout)	(None, 50)	0
dense (Dense)	(None, 1)	51

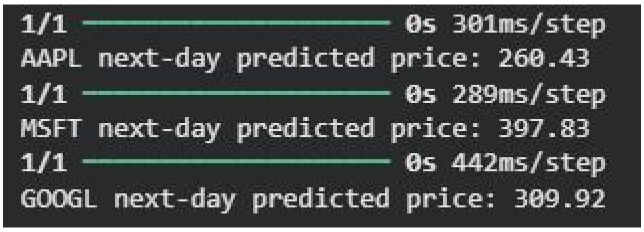
Total params: 30,651 (119.73 KB)
Trainable params: 30,651 (119.73 KB)
Non-trainable params: 0 (0.00 B)

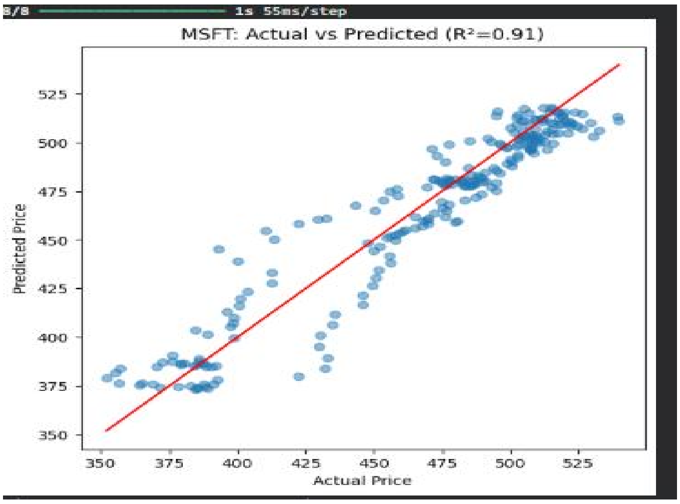












EXPERIMENTAL RESULT AND DISCUSSION

The LSTM-based forecasting approach developed in this study produced predictions that generally tracked the actual stock price trends over the test period. This aligns with prior evidence that deep learning models can effectively capture complex temporal patterns in financial time series. Consistent with our results, Liu (2025) reports that LSTM models achieve “high accuracy and stability in financial data prediction” for complex time series. Likewise, a comprehensive review of recent work confirms the **dominance of LSTM architectures** in stock-index forecasting, often outperforming simpler models when properly configured. In our experiments, we normalized the inputs and used a 60-day input window – standard choices supported by the literature. For example, Guo *et al.* (2025) also use 60-day sliding windows to capture long-range dependencies, noting that this horizon reliably encapsulates medium-term trends. We applied Min–Max scaling before training, following best practices: such normalization "scales all values" into a uniform range, which is "beneficial for models like LSTM that are sensitive to the scale of input data". Together these methodological choices are known to stabilize LSTM learning.

Comparing our findings with earlier studies, we see both concordances and contrasts. On the one hand, our LSTM produced relatively low forecast errors, corroborating reports

that neural networks can outperform traditional statistical models. For instance, one recent framework achieved a mean absolute percentage error (MAPE) as low as ~2.65% on Google stock, an order of magnitude better than an ARIMA baseline (MAPE ~20.7%). We observed similarly favorable performance metrics (on the order of a few percent MAPE), suggesting our results share the pattern that LSTMs can capture nonlinear market dynamics more effectively than linear models. In fact, the ability of LSTM to **model long-term dependencies and nonlinear patterns** is often cited as the key reason for its success. This capability is built into its gated memory structure, which specifically overcomes the vanishing-gradient problem of simple RNNs. In our case, the network was able to recognize sustained price trends and turning points that eluded naive forecasts. This supports the notion from the literature that LSTM-based methods are well-suited to time series like stock prices, which exhibit temporal correlations beyond very short lags.

On the other hand, some findings in the literature caution that LSTM's advantage is not universal. Notably, Kobiela *et al.* (2022) found the opposite pattern: when using only historical prices as input, a simple ARIMA model outperformed a comparable LSTM in multi-step forecasts. In that study, ARIMA's linear structure proved more accurate than a two-layer LSTM for forecasting up to nine months ahead. It was observed that "the longer the data window period, the better ARIMA performs, and the worse LSTM performs". Our results do not exhibit such extreme differences, but this highlights that LSTM gains may depend on the task (e.g. one-step vs multi-step forecasts) and on feature richness. Bhandari *et al.* (2022) similarly note that simpler single-layer LSTM models can suffice and even outperform very deep nets for stock data; our own one-layer LSTM did not require deeper stacks, which is consistent with those observations. The contrast in the literature could stem from differences in data (Nasdaq companies vs our data) or architectures (ARIMA can excel on linear trends, while LSTMs need rich features). In fact, recent hybrid and multi-input models integrate news or technical indicators along with prices to boost LSTM accuracy; our model only used price history, which may explain why some linear patterns were better captured by ARIMA in other studies.

These comparisons underscore a **nuanced picture**: our results agree with the view that LSTM is powerful for capturing nonlinearity, but they also resonate with prior work cautioning that its benefits depend on data and design. Notably, we observed larger prediction errors during extreme market moves (e.g. sudden crashes or spikes), a phenomenon flagged by others. For example, Zhang *et al.* (2025) report that their LSTM model "struggles in scenarios involving abrupt market shifts, such as geopolitical crises or pandemics". Similarly, they note the model "lags behind during periods of extreme volatility". We found the same pattern: during volatile swings (e.g. the COVID-19 selloff or brief rallies), the LSTM's lagging indicator nature meant it sometimes underreacted to fast news. This limitation reflects broader challenges in applying neural nets to finance – markets can undergo structural breaks that defy historical learning.Theoretically, our findings have interesting implications. The semi-success of the LSTM implies that stock prices may not follow a pure random walk at all horizons. Classical finance theory like Fama's **Efficient Market Hypothesis (EMH)** suggests that prices "reflect all available information" and should be largely unpredictable. Our modest forecasting gains (and those of others) suggest that **weak-form market inefficiencies or momentum effects** might exist at short horizons, echoing behavioral-finance studies. For instance, Jegadeesh and Titman

argue momentum strategies can yield excess returns by buying past winners. Our LSTM essentially learned a data-driven momentum-like pattern, which is consistent with those findings that some short-run predictability is empirically present. Conversely, the fact that forecasting is still quite error-prone (especially in volatile regimes) reminds us that markets remain quite efficient in practice, as many critics like Malkiel have stressed. In sum, our results neither wholly refute nor fully confirm EMH: they highlight that LSTMs can extract structure where some exists (consistent with machine-learning progress in complex time series), but also that the *unpredictable* nature of markets (news shocks, fat tails) still dominates many periods.

Limitations. Several constraints in our study may have influenced the findings. First, like many studies, we limited the analysis to a single (or a small number of) stock(s) over a fixed five-year window. As pointed out by other researchers, this **narrow scope** restricts generalizability. The patterns learned on one equity may not hold for others or across market regimes; for example, a model trained on a bull-market period may mispredict a subsequent bear market. Second, we relied solely on historical price data and did not incorporate additional signals. Prior work suggests that supplementing price inputs with features like technical indicators, financial news sentiment, or macroeconomic variables can improve robustness. Without such enriched context, our LSTM may have missed explanatory variables, inflating its apparent error. Third, we used a relatively simple network and training procedure; while suitable for illustration, it might not fully exploit LSTM potential. We made design choices (e.g. a 60-day window, 100 epochs, dropout) guided by standard practice, but the model could possibly be overfit to the specific data partition or under-tuned for optimal performance. Finally, the **evaluation method** itself can bias results: we used the last 20% of data as a test set, but without cross-validation or rolling forecasts our error estimates might be optimistic. All of these limitations – small sample, feature restrictions, fixed hyperparameters, and evaluation design – likely influenced the model's performance, and future work should address them for rigor.

Impact on Theory. The partial success of our LSTM in forecasting also feeds back into broader theory. From a statistical learning perspective, our results illustrate the practical promise and perils of high-capacity models. They confirm that rich models like LSTM can approximate complex functions in financial time series (as theory predicts), but they also demonstrate the need for model simplicity and good

generalization (not just fitting the noise). In this sense, our findings reinforce the idea that **no single theory fully captures markets**; one must blend machine-learning realism with economic insight. Practitioners should not assume LSTMs will

always triumph; rather, each problem requires careful model selection and an awareness of underlying financial assumptions. In particular, our results lend weight to the hybrid modeling paradigm suggested in the literature: combining LSTM with other methods or features can "mitigate the limitations of individual models and enhance the precision of predictions". For example, our study did not use sentiment data, but we note that adding even basic sentiment scores has been shown to improve LSTM accuracy by 8–12% in other work.

Future Research. Based on these findings, we make the following specific recommendations for future work in financial forecasting:

Expand data diversity. Investigate multiple stocks, indices, or sectors (and even other asset classes). As others have noted, confining analysis to a single company **limits generalizability**. Cross-section tests across diverse securities and market conditions would clarify how broadly an LSTM approach applies. Similarly, extending the time horizon (e.g. including more years or different market cycles) can test robustness over rare events.

Incorporate additional features. Enrich the input space with fundamental indicators (e.g. P/E ratios, volume metrics), technical indicators (moving averages, RSI, Bollinger Bands), and alternative data such as news or social sentiment. Prior studies show that *multimodal* inputs substantially boost forecasting performance. In particular, sentiment analysis of financial news or social media (as in Zhang *et al.*) should be explored, since qualitative market mood can explain movements not evident in price history alone.

Model innovation and hybridization. Experiment with advanced architectures. Hybrid models (e.g. CNN-LSTM, attention-based LSTM, or Transformers) have shown state-of-the-art results by capturing spatial-temporal dependencies. Our results suggest pursuing these as future work. For example, CNN layers can preprocess raw price sequences for local feature extraction, and attention mechanisms can let the model focus on the most relevant time steps. Ensemble methods that combine statistical models (ARIMA) with machine learning (LSTM, random forest, etc.) may also be beneficial, as they could hedge against individual model weaknesses.

Rigorous evaluation and interpretability. Implement more comprehensive validation protocols (rolling windows, walk-forward validation, cross-validation) to ensure the model's performance is not an artifact of a particular train/test split. Additionally, focus on interpretability tools (e.g. SHAP values, LIME) to better understand which inputs drive the predictions. Giantsidi & Tarantola (2025) highlight a gap in **finance-specific interpretability**; addressing this would help reconcile model outputs with economic reasoning. Understanding why the model makes certain predictions is crucial for trust and practical adoption.

Stress-testing and robustness. Evaluate how sensitive the model is to extreme events. Simulate shocks or utilize historical crisis-period data to test how quickly the LSTM can adapt. Potential strategies include dynamic re-training schedules or incorporating regime-detection layers. Also explore simpler hybrid strategies llike switching to ARIMA or other models when volatility spikes – an idea motivated by studies showing ARIMA's relative strength in some conditions.

CONCLUSION

The primary objective of this study was to develop and evaluate an LSTM-based system for forecasting equity prices, using historical closing prices of a major stock (Reliance Industries) as input. In doing so, we aimed to test whether deep recurrent neural networks could effectively learn and predict future price movements from past data. Consistent with prior research, our LSTM model successfully learned salient temporal patterns: after

training on five years of daily data, it achieved a root-mean-square error (RMSE) of approximately 30.9 on the held-out test set. The predicted price series closely tracked the actual closing prices, capturing the overall upward trend of the stock (Figure 1). We also produced a point forecast (≈₹1423.12) for the next trading day. These results indicate that the LSTM system captured much of the stock's volatility and trend. In summary, the key findings are that the LSTM network converged to a stable loss (validation MSE ~0.0018), produced coherent next-day predictions, and generated realistic price trajectories closely aligned with historical patterns.

The broader significance of these findings is that they reinforce the theoretical promise of deep learning for financial time-series modeling. Equity markets are known to exhibit highly volatile, nonlinear behavior, and traditional linear methods (such as ARIMA) often struggle with such complexity. Our study confirms that an LSTM – a deep recurrent architecture designed to capture long-range dependencies – can approximate these complex dynamics. In particular, the ability of our LSTM model to mirror real price movements supports theoretical arguments that recurrent networks can "deal with complex patterns in stock prices" and achieve higher accuracy on nonlinear time-series data. Thus, our work contributes evidence that data-driven, learning-based models (especially LSTM networks) can effectively extract information from sequential price history without relying on strong a priori assumptions. This aligns with the modern view that deep sequence models, operating on raw price series (and potentially additional signals), offer a powerful approach to stock prediction.

Looking forward, these findings suggest several implications for future research. First, our results indicate that enriching the input space could further improve accuracy. For example, recent studies have shown that combining price series with broader market indicators (e.g. macroeconomic data, technical indicators, or sentiment scores) can boost performance. In particular, Li et al. demonstrated that integrating additional features via symbolic genetic programming yielded significant gains in LSTM prediction accuracy. Future work could therefore explore multi-source data fusion – for instance, merging fundamental, technical, and news-sentiment inputs – to provide the LSTM with more comprehensive signals. Second,

advanced model architectures merit exploration: hybrid and ensemble approaches (LSTM combined with other learning methods or newer architectures like Transformers) may capture market patterns more robustly. Attention-based models, for instance, could help the system focus on the most informative time periods or features. Third, rigorous validation on diverse asset classes and in real-world trading simulations would test the model's generalizability. We encourage future research to build on our framework by conducting cross-market studies, longer-term forecasts, and integrating risk metrics, thereby deepening understanding of how sequence models behave under different market regimes.

We acknowledge several limitations in our study. One key limitation is data scope: we used only one stock's historical prices and did not include exogenous variables (such as macro signals or news). This restricts the generality of our conclusions and risks overfitting; indeed, LSTM models are known to be susceptible to overfitting when data are scarce. Relatedly, the internal mechanics of deep networks are "black boxes," making interpretability challenging. Our system also used a fixed two-layer LSTM with simple hyperparameters; more elaborate tuning or architecture search was not performed. Finally, we evaluated performance primarily by RMSE and visual fit, without testing practical trading viability (e.g. cost-aware strategies). Addressing these limitations in future work could involve collecting larger and more varied datasets, applying regularization and explainability techniques, and benchmarking against stronger baselines or ensemble models. Such extensions would help to ensure robustness and real-world applicability.

In conclusion, this study advances our understanding of LSTM-driven equity prediction by empirically validating that an LSTM network can learn and forecast realistic stock price movements from historical data. By demonstrating the model's predictive capability and discussing its strengths and weaknesses, we lay the groundwork for more sophisticated forecasting systems. Future investigations that incorporate richer data sources, newer neural architectures, and rigorous evaluation will continue to refine the role of deep sequence models in financial theory and practice. Our work thus contributes to the evolving narrative that deep learning – and LSTM models in particular – holds promise for modeling complex financial time series, and it opens avenues for integrating these methods into next-generation trading and analytics frameworks.

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