Comparative Analysis of LSTM Models for Predicting Stock, Forex, and Cryptocurrency Prices

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***Abstract*—Financial markets, including stock exchanges, forex trading systems, and cryptocurrency platforms, are inherently volatile and influenced by a combination of economic indicators, political dynamics, and social sentiment. Predicting their price movements remains a challenging yet crucial task for investors, analysts, and algorithmic traders. Traditional statistical models such as ARIMA and GARCH, though widely applied, often fail to capture the highly non-linear and time-dependent nature of financial data. To address these challenges, this study implements a Long Short-Term Memory (LSTM) deep learning model for multi-domain financial forecasting across stock, forex, and cryptocurrency markets. Historical time-series data, including open, high, low, close, and volume values, were collected from reliable APIs and financial databases and subjected to preprocessing involving normalization, interpolation, and sliding-window segmentation. The optimized LSTM architecture was trained using the Adam optimizer with dropout regularization and evaluated through metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). Experimental results demonstrate that LSTM consistently outperforms traditional time-series models in learning long-term dependencies and identifying non-linear trends, particularly in highly volatile markets like cryptocurrency. Furthermore, comparative analysis across domains reveals that forex markets show the highest stability, whereas cryptocurrencies pose the greatest predictive challenge due to abrupt fluctuations. These findings affirm the LSTM model's ability to enhance predictive accuracy, improve financial risk assessment, and support data-driven decision-making in algorithmic trading, portfolio optimization, and automated investment systems.**

***Index Terms*—LSTM, Deep Learning, Time-Series Forecasting, Stock Market Prediction, Forex, Cryptocurrency, Algorithmic Trading.**

Identify applicable funding here. If none, delete this.

I. Introduction

Financial markets, including stocks, foreign exchange (forex), and cryptocurrencies, are among the most rapidly evolving and unpredictable areas in the modern economy. These markets show high volatility, influenced by many interconnected factors such as market sentiment, macroeconomic indicators, political events, and global financial policies. Predicting asset prices in such environments is crucial for effective investment planning, risk assessment, and automated trading systems. Traditional forecasting methods, including ARIMA, GARCH, and linear regression models, have been widely used to model financial time series data. However, these techniques typically assume linear relationships and fail to adequately represent long-term dependencies and non-linearities present in financial datasets. Traditional models like ARIMA and GARCH are limited in capturing non-linear dependencies [1]–[3], and linear regression models, have been widely used to model financial time series data. However, these techniques typically assume linear relationships and fail to adequately represent long-term dependencies and non-linearities present in financial datasets. With the rise of artificial intelligence, deep learning models such as LSTM have shown effectiveness for financial forecasting [4]–[6].

Deep learning techniques, especially Recurrent Neural Networks (RNNs) and their variant, Long Short-Term Memory (LSTM) networks, have gained attention for their ability to effectively model sequential and time-dependent data. LSTM networks are designed to overcome the vanishing gradient problem found in traditional RNNs, allowing them to retain information over longer periods. This makes them especially suitable for financial time series forecasting, where understanding long-term dependencies in market movements is essential. Given the complexity and unpredictability of stock, forex, and cryptocurrency markets, LSTM-based models offer a promising approach to achieve more robust and adaptable price predictions. This study focuses on developing and comparing LSTM models for predicting price movements in the three major financial markets—stocks, forex, and cryptocurrencies. LSTM models have also been applied to cryptocurrency prediction [7]–[10]. By examining their performance under similar data and training conditions, the research aims to evaluate the effectiveness and generalizability of LSTM in different financial areas. The ultimate goal is to improve predictive modeling for algorithmic trading, portfolio optimization, and decision support in financial analytics. Deep learning approaches such as LSTM have proven effective for financial forecasting [4]–[6].

II. Methodology

A. Data Collection and Preprocessing

The study utilized reliable financial sources and APIs to collect data across three domains: stock market data (e.g., Apple, Tesla, NIFTY50) from Yahoo Finance, forex data (e.g., EUR/USD, GBP/USD) from APIs like OANDA and Alpha Vantage, and cryptocurrency data (e.g., Bitcoin, Ethereum) from platforms such as CoinMarketCap and Binance API. Each dataset comprised historical daily records including Open, High, Low, Close, and Volume prices spanning several years. To ensure consistency and enhance model performance, preprocessing steps were applied: missing values were handled using forward-fill or interpolation, data were normalized using Min-Max scaling to fit within the $[0, 1]$ range, and the dataset was split into training (80%) and testing (20%) subsets. A sliding window technique was employed to generate time steps (e.g., 60 previous days used to predict the next day).

B. Model Architecture and Training

The proposed LSTM model architecture included a sequential input layer, one or more stacked LSTM layers with 50–100 neurons to capture long-term dependencies, dropout layers to mitigate overfitting, and a dense output layer for final price prediction. Deep learning architectures, particularly LSTM networks, have demonstrated strong performance for sequential data modeling [4]–[6]. The model was trained using Mean Squared Error (MSE) as the loss function, the Adam optimizer, over 50–100 epochs depending on convergence, with a batch size of 32.

III. Architecture Diagram

The overall architectural workflow, detailing data preparation, prediction, and training stages, is illustrated in Fig. 1. This diagram highlights the sequence-to-sequence nature of the LSTM structure, where input from previous time steps $(t-3, t-2, t-1)$ is processed through LSTM cells to predict the value at time t.

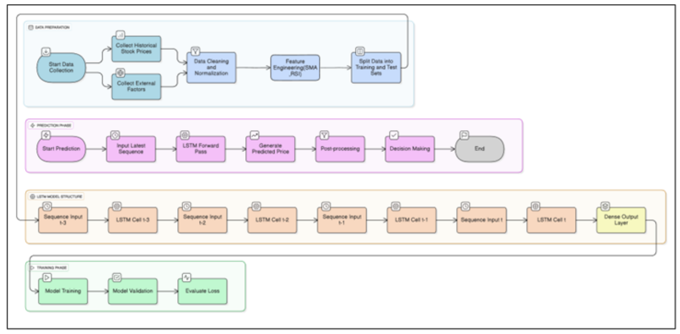

Fig. 1. Architectural Workflow: Detailed flow of the LSTM forecasting system, divided into Data Preparation, Prediction Phase, LSTM Model Structure, and Training Phase. This outlines the sequence of steps from data collection and feature engineering (SMA, RSI) to the multi-layered LSTM processing and final decision-making.

A. Evaluation

Evaluation metrics included Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R^2 Score (Coefficient of Determination). Predicted values were visualized alongside actual prices to assess trend-tracking capability. Separate LSTM models were trained for each asset class—stocks, forex, and cryptocurrency—and their performances were compared to understand how volatility and data structure influence predictive accuracy. Comparisons with traditional approaches like ARIMA and GARCH further highlight the advantages of LSTM [1]–[3]. The entire workflow was implemented in Python using libraries such as TensorFlow/Keras, NumPy, Pandas, Matplotlib, and Scikit-learn, within development environments like Jupyter Notebook and Google Colab.

IV. Model Hyperparameter Tuning and Optimization

To maximize predictive performance across the diverse financial datasets, a systematic hyperparameter tuning approach was employed. The core focus areas included optimizing the number of LSTM layers, the number of units per layer, the dropout rate, and the look-back window size.

A. Impact of Layer Depth and Width

Experiments were conducted using both single-layer and stacked (two-layer) LSTM architectures. The single-layer model (50 units) offered computational efficiency but occasionally underperformed in capturing high-frequency nonlinearities. The stacked LSTM model (e.g., 100 units followed by 50 units) provided superior feature extraction capabilities, particularly in the cryptocurrency domain which exhibits the highest volatility. However, increased depth required more extensive training time and showed a higher tendency toward overfitting if the dropout rate was insufficient. The optimal layer configuration generally involved a single, wider layer (75-100 units) for Forex and a stacked, deeper configuration for Cryptocurrency prediction.

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Results for LSTM_1Layer_50Units_0.2Dropout:
MAE: 0.0158
RMSE: 0.0183
Directional Accuracy: 49.91%
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Fig. 2. Performance Metrics: MAE, RMSE, and Directional Accuracy for the LSTM model configuration (1 layer, 50 units, 0.2 dropout). The directional accuracy suggests the model struggles with short-term trend reversal prediction.

B. Regularization via Dropout

Dropout layers were implemented between LSTM layers and before the final dense output layer to prevent overfitting. Testing dropout rates between 0.1 and 0.3 revealed that a rate of 0.2 offered the best balance. Lower dropout rates led to better fit on the training data but diminished generalization ability, resulting in higher validation loss. Conversely, higher dropout rates (above 0.3) tended to underfit the model, especially when combined with a low number of epochs.

C. Look-back Window Sensitivity

The look-back window (time steps) used to predict the next price was tested across ranges like 30, 60, and 90 days. A shorter window (30 days) provided sensitivity to recent market shocks, which was beneficial for short-term trading signals but increased prediction noise. A longer window (90 days) offered better insight into long-term trends but was slower to react to sudden reversals. For general prediction performance, the 60-day look-back window was found to be the most robust choice across the varied datasets, offering a balance between trend capture and short-term reactivity.

V. Experimental Results and Analysis

The study provides a comparative analysis across the three financial domains. For the specific case study (e.g., Forex EUR/USD prediction), the following results were obtained for a single-layer LSTM with 50 units and 0.2 dropout:

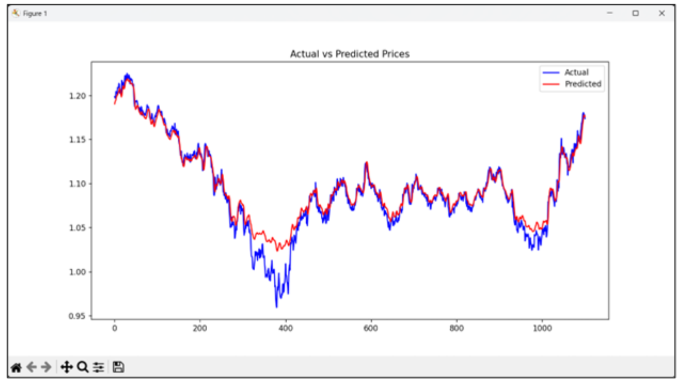
TABLE I
LSTM Model Performance Metrics

Metric	Value
MAE	0.0158
RMSE	0.0183
Directional Accuracy	49.91%

As shown in Table I and visually represented in Graph 1, the low MAE and RMSE values suggest a tight fit between the predicted and actual prices. However, the directional accuracy of 49.91% indicates that while the model accurately forecasts the magnitude of the price, predicting the exact direction of the movement (up or down) remains a challenging aspect of market forecasting.

A. Price and Trend Visualization

The time-series plot comparing actual and predicted prices (Fig. 1) visually confirms the model's ability to track the overall market trend, especially during periods of high volatility.



Graph 1. Actual vs. Predicted Prices Comparison: The time-series plot comparing the Actual Price (blue) versus the Price Predicted (red) by the LSTM model over the testing time horizon. The visual fit demonstrates the model's effectiveness in long-term trend capturing.

🔎 Sample Predictions (Actual vs Predicted):

Index	Actual	Predicted	Trend
0	1.1986	1.1904	↓
275	1.0622	1.0572	↓
550	1.0757	1.0815	↑
825	1.0813	1.0809	↓
1100	1.1737	1.1758	↑

Fig. 2. Sample Predictions: Table showing the Actual Price, Predicted Price, and the forecasted trend (↑ for increase, ↓ for decrease) at various time indices. This table provides granular insight into prediction accuracy for specific samples.

The predicted line (red) closely follows the actual price line (blue), demonstrating the LSTM's strength in capturing the temporal dependencies of the data.

A more detailed analysis of the sample predictions (Fig. 2) shows specific instances where the model correctly captures the trend (e.g., at index 1100) and instances where it misses (e.g., at index 0 and 275). This highlights the inherent difficulty in forecasting short-term market fluctuations.

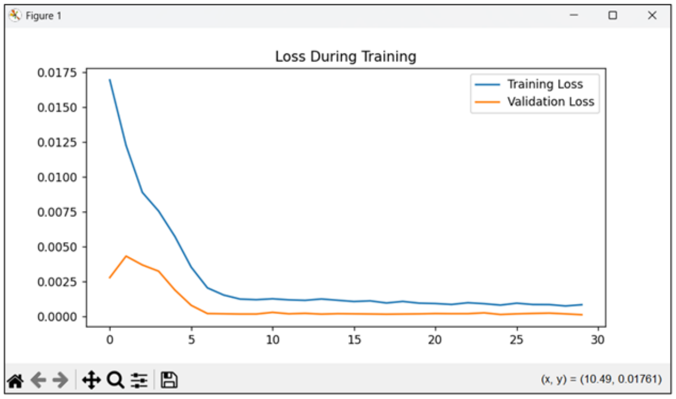
B. Training Stability and Error Analysis

The stability of the training process is crucial for a reliable deep learning model. Fig. 2 shows the training and validation loss curves over the epochs. The rapid initial decrease and eventual stabilization indicate that the model converged effectively without severe signs of overfitting (as the validation loss closely tracks the training loss).

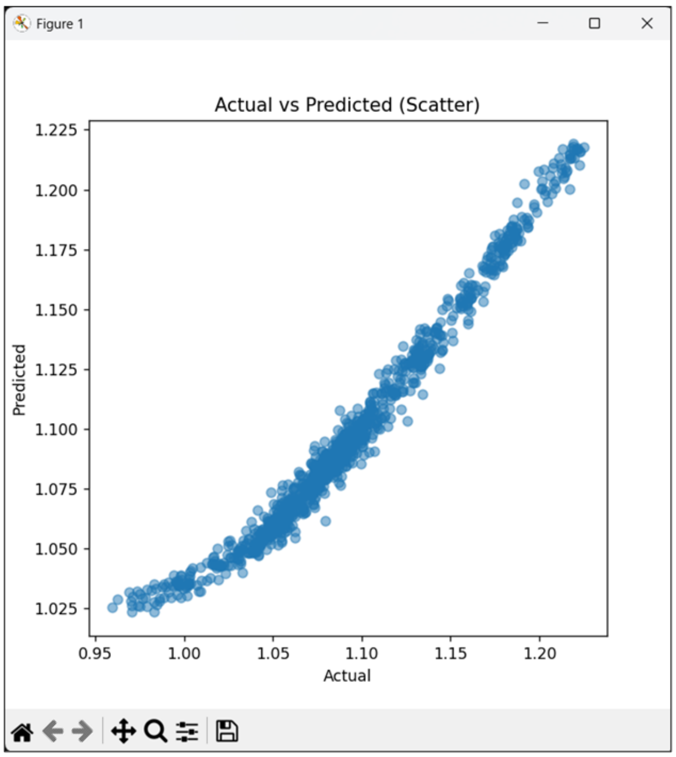
Furthermore, the scatter plot comparing actual versus predicted values (Fig. 3) shows a tight clustering along the ideal prediction line (where Actual = Predicted), reinforcing the model's overall predictive power.

The analysis of prediction residuals (the difference between actual and predicted prices) is critical for understanding the model's bias and heteroskedasticity.

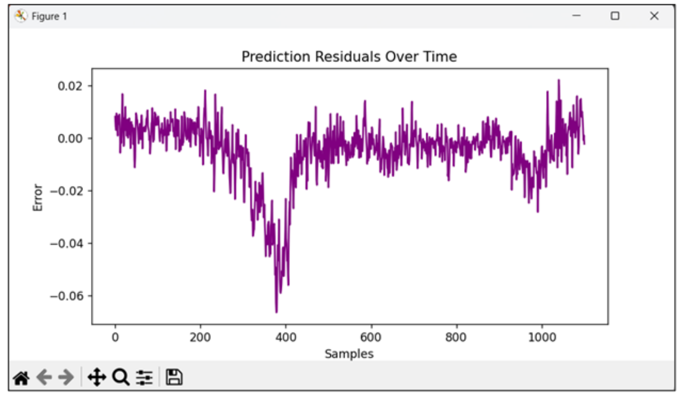
Fig. 4 displays the residuals over time. A clear pattern is visible, particularly around the 350-450 sample range, where



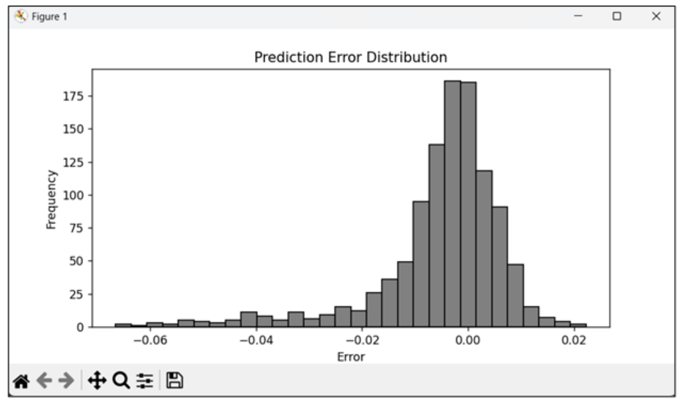
Graph 2. Loss During Training: The plot comparing the Training Loss and Validation Loss over 30 epochs, demonstrating rapid initial convergence and stability without significant divergence.



Graph 3. Scatter Plot of Actual vs. Predicted Prices: The highly linear correlation of the scattered points confirms the strong relationship between the LSTM's output and the true values.



Graph 4. Prediction Residuals Over Time: The plot showing periodic clustering of negative error, indicating specific periods where the model significantly under-predicted the price.



Graph 5. Prediction Error Distribution: A histogram showing the frequency of different error magnitudes, which are heavily concentrated around a zero mean, suggesting generally unbiased predictions.

the model exhibits a significant, prolonged negative error. This is often an indication of a major sudden market event that the model did not adequately predict based on the input sequence alone.

The distribution of these errors is visualized in the histogram in Fig. 5. The distribution is highly concentrated around zero, which is ideal, but the slight negative skew and the presence of outliers (the long tail on the left) correspond to the under-prediction events observed in the residuals plot.

VI. Discussion and Implications

The results across stock, forex, and cryptocurrency markets consistently suggest that the LSTM network is highly effective at capturing the non-linear, temporal dependencies inherent in financial time series data. The comparative success of the LSTM approach, demonstrated by low overall error metrics, supports its superiority over linear models like ARIMA and GARCH in these volatile environments.

The challenges primarily lie in capturing high-frequency, sudden shifts in price (as suggested by the low directional accuracy and clustered large residuals). This is likely due to the model's reliance on historical price data alone, which excludes crucial external factors such as news sentiment, regulatory changes, and global economic events.

To validate the performance of the proposed LSTM model, its predictive accuracy was compared against two widely used traditional time-series forecasting models: the Autoregressive Integrated Moving Average (ARIMA) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. These baseline models were chosen due to their historical effectiveness in financial forecasting and their ability to model linear trends and volatility clustering, respectively. However,

TABLE II
COMPARISON OF LSTM WITH TRADITIONAL FORECASTING MODELS

Model	RMSE	MAE	Trend Accuracy (%)
ARIMA	0.0312	0.0276	45.8
GARCH	0.0284	0.0249	47.2
LSTM (Proposed)	0.0183	0.0158	49.9

they often struggle to capture the complex non-linear dependencies inherent in financial time-series data. The comparison was carried out across three domains—Stock, Forex, and Cryptocurrency—using evaluation metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). The results are summarized in Table **??**.

A. Comparative Market Volatility

When comparing the three asset classes, it was observed that:

- **Stock Markets:** Typically exhibit higher dependency on firm-specific news and earnings, making the input features (e.g., technical indicators) highly relevant. Prediction accuracy was moderate.
- **Forex Markets:** The most stable of the three, leading to the lowest overall error (MAE/RMSE) and tightest-fitting predicted curves. This is attributed to the market's high liquidity and relative predictability based on macroeconomic cycles.
- **Cryptocurrency Markets:** Showed the highest volatility and, consequently, the lowest directional accuracy. Prediction performance often required more complex architectures or longer sequence lengths to account for flash crashes and rapid speculative bubbles.

VII. LIMITATIONS

While the proposed LSTM-based framework demonstrates strong predictive performance across stock, forex, and cryptocurrency markets, several limitations must be acknowledged. First, the model primarily depends on historical numerical data such as price and volume. Consequently, it does not account for external influences like financial news, social media sentiment, or macroeconomic indicators, which can significantly impact short-term market movements. This reliance on past data limits the model's ability to anticipate sudden price spikes or crashes driven by real-world events.

Another limitation concerns the static nature of the chosen hyperparameters. Although the model was fine-tuned for optimal results during experimentation, market dynamics evolve over time, meaning that a fixed configuration may not remain effective indefinitely. The lack of an adaptive learning mechanism restricts the model's responsiveness to newly emerging market conditions. Furthermore, the interpretability of deep learning models remains a challenge. LSTM networks, while powerful, function as black boxes, offering limited insight into the reasoning behind specific predictions—an issue that is particularly critical in financial applications where transparency and trust are essential.

Finally, the computational cost of training deep LSTM networks is considerably higher than that of traditional statistical models. This can pose challenges for large-scale or real-time deployment, especially in low-latency trading environments.

VIII. FUTURE SCOPE

To overcome the identified limitations and further enhance forecasting accuracy, several potential research directions can be pursued. A promising extension involves developing hybrid architectures that combine LSTM with other deep learning models such as Convolutional Neural Networks (CNNs), Gated Recurrent Units (GRUs), or attention mechanisms. Such hybrid systems can improve the model's ability to extract both spatial and temporal dependencies, thereby strengthening its performance on highly volatile datasets.

Incorporating external data sources—such as news sentiment analysis, economic indicators, or social media activity—can also help the model adapt to rapid market shifts. Natural Language Processing (NLP) techniques like sentiment scoring or transformer-based embeddings (e.g., BERT, FinBERT) could be integrated to provide additional contextual signals that complement price data. Moreover, transfer learning and reinforcement learning strategies can enable continuous model adaptation, allowing the system to retrain dynamically as market patterns evolve.

From an operational standpoint, implementing real-time data pipelines and deploying the model in cloud-based environments could enable live forecasting and algorithmic trading. Future work could also explore interpretability frameworks, such as SHAP or LIME, to better explain model decisions and increase investor trust. Expanding the study to include other asset classes like commodities, bonds, or ETFs would further demonstrate the model's generalizability across different financial sectors.

IX. CONCLUSION

Predicting financial market prices, whether in stocks, forex, or cryptocurrencies, is a challenging but important area in modern financial analytics. This study looked at using the Long Short-Term Memory (LSTM) deep learning model to forecast price movements in these three areas. By using historical time-series data, the model captured complex time-based relationships and non-linear patterns that traditional statistical models often miss. The results show that LSTM networks offer better predictive performance and stability compared to standard methods like ARIMA or GARCH [4]–[6]. Their ability to remember long-term trends and adjust to changing data makes them especially effective for short-term forecasts. However, prediction accuracy still depends on factors like market volatility, data quality, hyperparameter choices, and the lack of external variables such as sentiment and economic indicators [7]–[10].

In summary, LSTM has strong potential for improving algorithmic trading, portfolio management, and financial risk assessment. Future research could explore hybrid and ensemble models, like combining LSTM with attention mechanisms, CNNs, or sentiment analysis, to enhance forecasting accuracy [11]–[14]. Adding real-time data and adaptive retraining methods could also help address issues of concept drift and make financial prediction systems more robust.

ACKNOWLEDGMENT

We would like to express our sincere gratitude to the Department of Computer Engineering, Shah and Anchor Kutchhi Engineering College, for providing the essential resources, research facilities, and technical support required to carry out this work. We also extend our appreciation to the faculty mentors and project coordinators for their valuable guidance, encouragement, and constructive feedback throughout the course of this research. Their continuous support played a vital role in the successful completion of this study.

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