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Research paper

Predicting financial asset prices with neural network: a comparative study of neural network's effectiveness in financial decision-making

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Abstract

Investing requires deep knowledge of complex financial markets, making it incredibly tedious to predict inflation and deflation. Predictive conventional models like ARIMA and GARCH do not accurately capture the non-linearity and volatility presented in financial datasets. This research examines the different forms of predictive assets, real estate, stocks, commodities, bonds, and cryptocurrency using Long Short-Term Memory (LSTM) Neural networks. The primary focus of this research is to assess the valuable prediction capabilities of LSTM across assets and its integration with financial decision-making. According to the empirical results, deep learning LSTM models give better outcomes with equities and gold, with the R2 indicator reaching over 99% alongside a low RMSE. LSTMs had an over 100% MPE prediction error rate for other assets during the test phase, making it harder to predict intensely volatile assets. The model's verification transfers residual autocorrelation, showing that it can enhance forecasting performance with detailed macroeconomic indicators and sentiment analysis data. Studies show that LSTMs are effective in high-frequency markets with non-linear price changes, but they require special attention to balance interpretability and overfitting. Despite the progress that has been achieved in utilizing neural networks for financial forecasting, hybrid models integrated with XAI are recommended to improve efficiency and real-world applicability. These results contribute to the growing domain of AI-powered finance by offering additional means for many investors, analysts, and decision-makers who wish to utilize data for market speculation.

Keywords: *Neural Networks: ARIMA; GARCH; LSTM; Financial Decision Making; Prediction.*

1. Introduction

Financial markets are highly dynamic, influenced by macroeconomic trends, geopolitical events, investor sentiment, and technological advancements. Accurate price forecasting is critical for investment strategies, risk management, and overall market efficiency. Traditional econometric models like ARIMA and GARCH have long been relied upon for financial analysis. However, these models struggle with capturing the nonlinear and volatile nature of financial markets. Recent advancements in artificial intelligence (AI) and machine learning (ML), particularly deep learning techniques such as neural networks, have enhanced financial forecasting through improved pattern recognition and data modelling. Among these, Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), have gained prominence for capturing sequential dependencies and long-term patterns in financial time-series data. Financial forecasting has progressed from fundamental and technical analysis to econometric models like ARIMA and GARCH, which struggled with market shifts. Machine learning (ML) models like SVMs and Random Forests improved predictions, but deep learning models, particularly LSTM-based RNNs, now dominate by capturing sequential dependencies. Despite AI's superior performance, challenges like overfitting and interpretability remain.

Globalization and technology have made financial decision-making complex. AI, big data, and algorithmic trading enhance traditional methods, with HFT exploiting market anomalies and alternative data refining investment strategies. While AI-driven finance improves diversification and risk analysis, challenges like automation bias, market volatility, and regulatory concerns persist, requiring a balance between innovation and transparency. Neural networks revolutionized forecasting by uncovering patterns in large datasets. LSTMs outperform traditional models in time-series forecasting, while CNNs and transformers enhance sentiment analysis using unstructured data. However, issues like overfitting, interpretability, and computational costs limit their adoption, necessitating further research and optimization.

Market complexity, macroeconomic fluctuations, and unpredictable behavior make forecasting difficult. Data quality issues, reliance on alternative sources, overfitting, and black swan events impact model reliability. Lack of transparency in neural networks raises regulatory concerns, while high implementation costs and ethical risks hinder AI adoption. Addressing these challenges is key to improving accuracy, adaptability, and trust in AI-driven finance. Technological advancements, globalization, and evolving regulations are reshaping financial markets. High-frequency trading, AI-driven strategies, and decentralized finance (DeFi) are replacing traditional trading models, increasing efficiency and amplifying volatility and systemic risks. Retail investors and social media-driven trends, like the GameStop short squeeze, have further disrupted market dynamics. Macroeconomic factors such as inflation, interest rates, and geopolitical tensions add to market uncertainties. To mitigate risks, financial institutions are adopting AI, predictive analytics, and blockchain. Innovation, regulation, and risk management will be key to navigating future market transformations.

Predicting financial asset prices is crucial for investments, economic policies, and risk management. Traditional models like ARIMA, GARCH, and CAPM struggle with market shocks and non-linearity. AI-driven neural networks, especially LSTMs, offer improved accuracy by identifying deep patterns in financial time-series data. However, challenges like market anomalies, algorithmic biases, and model interpretability persist. This study compares neural networks with standard forecasting models to assess their effectiveness in modern financial markets.

With financial markets becoming more complex, accurate asset pricing is vital for investors and institutions. Traditional models often fail to capture non-linearity and high-frequency data, leading to suboptimal investment decisions. Deep learning models like LSTMs show promise but remain underutilized. Specifically, LSTM-based models have the potential to redefine financial reporting conventions and affect regulatory monitoring. Reliable price predictions can facilitate fair value estimation under accounting standards such as IFRS 13 and Ind AS 113, particularly for Level 2 and Level 3 inputs where market prices are not observable. Further, regulatory organizations like SEBI or RBI could study how predictive analytics affect market stability, detection of systemic risks, and warning systems. With increasingly integrated AI tools in the financial infrastructure, transparency, interpretability of models will become more essential for compliance as well as protection of investors.

This research evaluates whether LSTMs outperform ARIMA, GARCH, and fundamental analysis, aiming to enhance risk management, portfolio returns, and real-world AI adoption in financial forecasting.

In this context, the following are the objectives of this study,

- To determine how precise neural networks are at estimating the prices of financial assets.
- To evaluate model validity using extensive validation checks like residual movement, correlation, regression analysis, etc.

2. Literature review

The dynamic nature of financial markets, having dependencies that are non-linear, volatile, and complex, makes it impossible for ARIMA, GARCH, and even linear regression methods to serve as reliable forecasting techniques. This is precisely why deep learning techniques, notably RNNs, LSTMs, CNNs, and even some transformer-based networks, have made market forecasting simpler and far more accurate about sequential data processing and the deep understanding of intricate market dynamics.

Later analyses have revealed how effective LSTM-based models are in financial forecasting. Gokulakrishnan et al. (2025) discuss how businesses perform better utilizing LSTM networks over conventional models because LSTMs can manage long-term dependencies and complexities of price movements. This personally benefits trading, financial decisions, and even risk management. Similarly, Pushkala et al. (2024) highlight comparisons between LSTM, Random Forest, and Linear Regression models, where it was found that LSTMs have the highest predictive precision when sentiment analysis and macroeconomic criteria are applied. Wen (2024) also stated that CNN, LSTM, and ANN models behave differently in financial datasets, supporting that LSTMs are the best at retaining long-term dependencies and reducing prediction errors.

A few researchers have delved into the usage of hybrid models of deep learning and how they can improve the level of accuracy in forecasting. Apte & Haribhakta (2024) study N-HiTS and N-BEATS models, which have started to gain traction, as they have much better results than traditional statistical models for non-linear market time series forecasting. Fabbri (2024) utilizes multi-layered sequential LSTMs (MLS-LSTM) in asset management and shows that introducing the Fama-French factors increased alpha generation by 45.26 percentage points, particularly for the cryptocurrency class of assets. Wang & Lu (2024) use the ISSA-BiLSTM-TPA model, which augments financial decision-making by combining attention and bidirectional dependency learning – this model's accuracy is far above standard deep learning models, but still lower than expected deep learning performance.

Other neural network models beyond LSTMs have been explored for financial forecasting. Guan et al. (2023) explored LSTM, GRU-LSTM, and Attention-LSTM and showed that while first first-mentioned styles fit the best, the Transformer-LSTM has the best generalization across varying datasets. Fang and Wang (2024) showed a new approach to solving the problem of decision-making within institutional investors and hedge funds due to the complexity of financial time series data under the CEEMDAN-CNN-LSTM method.

Neural networks' performance has also been assessed in the context of trading activities and the optimization of portfolios. Sermpinis et al. (2021) study the utilization of RNN, Multi-Layer Perceptrons (MLP), and Radial Basis Function (RBF) networks in trading and risk management and conclude that RNNs are the most profitable and robust class of networks in the context of financial turbulence. Likewise, Aldridge & Avellaneda (2019) prove that neural networks incorporating market indices such as the S&P 500 outperform classic buy-and-hold portfolios, further proving their usefulness in trading.

Most of the cited literature suggests that neural networks may be challenging to apply in the realm of financial forecasting. Oyewole et al. (2024) claim that data cleanliness in structure and the absence of bias steers data quality since neural networks tend to underperform with dirty structured financial data. Akinrinola et al. (2024) suggest that models of neural networks should be continuously refined and modified to respond to volatility in the market, as well as changes in the economic environment. Although deep learning models are highly regarded in financial forecasting, Medvedev (2023) argues that the need for robust efficiency from these neural networks is critical. Further investigation into the stability and interpretability of the models is necessary to improve the approach to financial forecasting.

The "black-box" characteristic of deep learning, which hinders its interpretability and acceptance, is another major concern. González-Cortés et al. (2024) and Baihaqi et al. (2023) argue that there must be a framework for Explainable AI (XAI) to make neural network predictions worthy of trust by investors, regulators, and financial institutions. In their paper, Kalaiselvi et al. (2018) outline opposition-based learning in backpropagation neural networks, which improves forecasting accuracy and reduces the number of computations needed.

Additionally, neural networks have been studied alongside other frameworks about models for pricing and assessing risks. Ndikum (2020) contends that AI techniques, especially neural networks, outperform the Capital Asset Pricing Model (CAPM) in out-of-sample testing, which suggests that AI models are more accurate and applicable. Aamodt & Torresen (2017) studied feedforward and echo state networks and concluded that more complex deep learning architectures outperform simpler ones in the accuracy of forecasting over longer intervals, while short-term predictions are best made by simpler neural models.

Deep learning-based finance predictions are becoming common. AI-enabled predictions have clearly shown the impact that social media sentiment, news sentiment, and macroeconomic factors have on the financial market. Oyewole et al.'s (2024) study reflects this trend. Singh & Kaushik (2020), on the other hand, use big data analytics and neural networks to explain the growing accuracy in market predictions, claiming that when such models are trained using deep learning on multi-structured data, they outperform conventional indicators.

Even with improvements in the field, many scholars highlight the difficulties and limitations in computational power for deep learning-based systems. Kalaiselvi et al. (2018) reiterate that for small businesses, implementing deep learning-based neural networks for predicting finance is challenging due to the high computational power and hyperparameter tuning needed. Ndikum (2020) specifies that having high-quality datasets and optimal model-building techniques makes financial forecasting with neural networks possible.

Existing research on LSTM models for financial forecasting has primarily concentrated on stock market predictions, with limited focus on the broader financial market, including bonds, commodities, and other asset classes. Additionally, most studies have been conducted in the context of foreign markets, with relatively little exploration of the Indian financial market. This creates a gap in understanding how LSTM models perform across diverse financial assets within the Indian context. The lack of comprehensive research on multiple asset classes limits the applicability of these models for holistic financial decision-making. This study aims to bridge this gap by expanding the scope beyond stock market predictions to include other key financial assets, offering a more comprehensive evaluation of LSTM models in the Indian financial landscape.

Though available studies mainly cover technical model comparisons, there is little research conducted on the macro-financial or regulatory consequences of AI-based forecasting. For instance, Ndikum (2020) indicates that neural networks can surpass CAPM, opening the possibilities for a shift from the practice of pricing risk and return and affecting capital adequacy estimates. Likewise, Baihaqi et al. (2023) highlight the significance of explainable models to drive accountability in disclosure statements.

From an accounting perspective, Chen & Wu (2024) provide the implications of predictive analytics for fair value measurement under IFRS standards. This means model outputs can impact not just portfolio optimization but also financial reporting, regulatory audits, and provisioning capital.

3. Methodology

This research focuses on the implementation of artificial intelligence, particularly the application of neural networks featuring Long Short-Term Memory (LSTM) models, and their effectiveness in predicting the prices of financial assets. It seeks to explore how these models manage market fluctuations, identify cycles, and improve precision in resolving issues of overfitting, excessive computational effort, and opacity in frameworks' operations. The purpose is to understand and assess the usefulness of neural networks in guiding financial decisions to their users and stakeholders, including analysts and financial institutions who aim at better forecasting and investment plans.

The study opts for a quantitative design, working with algorithms in the Python programming language to test the accuracy of predictions of the financial asset price using a long short-term memory (LSTM) network. The data is obtained from Bloomberg, which includes different asset classes, including stocks, crypto, commodities, bonds, and real estate. The dataset underwent basic preprocessing, which included changing dates to datetime type, chronologically ordering the data, eliminating invalid data, and applying feature engineering techniques. Important features with model predictive power, such as closing prices, moving averages, and daily returns, will be added to improve model performance. In preparing the data, the following steps will be included: scaling and normalization with MinMaxScaler, train-test splitting (80% training, 20% testing), and creation of sequences from 60-time steps to produce sequential data for the LSTM model. The architecture of the LSTM model will have two LSTM layers, overfitting dropout layers, and dense layers for output. The model was compiled using Adam optimizer with MSE loss function and was trained over several epochs with early stopping to enhance performance.

This study evaluates the accuracy and reliability of neural networks in predicting financial asset prices across multiple asset classes, including stocks, cryptocurrencies, commodities, bonds, and real estate. The research utilizes publicly available financial data and employs machine learning techniques in Python, with all data preprocessing, model training, and validation conducted using automated neural network models. The study emphasizes the absolute predictive accuracy of neural networks rather than comparing them with traditional forecasting methods. Performance assessment is carried out through comprehensive validation tests, including residual analysis, correlation analysis, and regression diagnostics, ensuring a rigorous evaluation of model reliability. While the study provides insights into the challenges of using neural networks in financial forecasting, it does not address external factors such as macroeconomic shifts, regulatory changes, or sentiment-driven market movements, focusing instead on the technical effectiveness of neural networks in processing and predicting financial time-series data.

Following data collection, we partitioned the dataset into training (80%) and testing (20%) subsets. This partitioning strategy ensures that neural network models learn from historical price movements while being evaluated on unseen data, allowing for a reliable assessment of predictive accuracy and generalization capability.

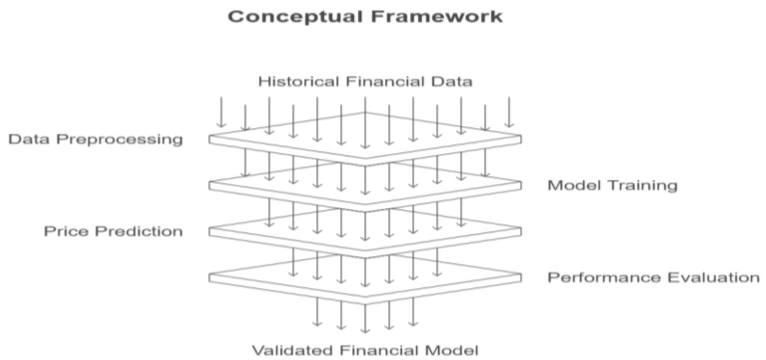


Fig. 1: Conceptual Framework.

This study utilizes machine learning and statistical tools for data processing, model training, and evaluation. The key instruments used include:

1) Python Programming Language – Used for data preprocessing, model training, and evaluation. Key libraries include:
- Pandas & NumPy: Data handling and feature engineering.
- TensorFlow & Keras: Building and training neural network models.
- Scikit-learn: Data scaling, train-test splitting, and model evaluation.
- Matplotlib & Seaborn: Data visualization for trend analysis and performance monitoring.
2) Bloomberg Terminal – The primary source for historical financial data covering stocks, cryptocurrencies, commodities, bonds, and real estate from January 1, 2015, to January 1, 2025.
3) MinMaxScaler (Scikit-learn) – Used to normalize financial data between 0 and 1 to improve neural network performance.
4) LSTM Neural Network Model (Keras/TensorFlow) – The deep learning architecture used to predict financial asset prices based on historical time-series data.
5) Performance Metrics for Validation – To assess the accuracy and reliability of predictions:
- Root Mean Squared Error (RMSE) – Measures prediction accuracy.
- Residual Analysis (Histogram, ACF, PACF, Ljung-Box Test) – Evaluates model fit.
- Pearson Correlation – Assesses the relationship between actual and predicted values.
- Regression Analysis (R^2, Coefficient Significance Tests) – Determines model reliability.

4. Data analysis and results

To provide a holistic view of LSTM model performance on various financial assets, this section tests the model on five asset classes: equities, cryptocurrencies, commodities, real estate, and bonds. Each of these classes has distinctive features, varying from liquidity and volatility to macroeconomic sensitivity, giving a heterogeneous test bed for model generalizability and robustness. The dataset consists of historical financial data sourced from Bloomberg over ten years (Jan 1, 2015 - Jan 1, 2025), which includes the following five asset classes:

1) Equities (Stocks) - Equity indices capture different segments of the Indian stock market by different market capitalization levels.
- Nifty 50 – Large-cap index of the fifty most capitalized companies.
- Nifty 500 – Covers the top five hundred companies, and is considered a broad market index.
- Nifty Midcap 150 – Represents mid-sized capitalized companies.
- Nifty Smallcap 250 – Features small capitalized, high-growth but volatile stocks.
2) Commodities
- Crude oil – The energy sector's most important utility product, highly volatile.
- Gold ETF – A highly capitalized asset used to hedge against inflation and market instability.
- Cryptocurrencies
- Bitcoin: The most traded cryptocurrency that experiences drastic price movements due to sentiments in the market and adoption globally.
- Ethereum: One of the top cryptocurrencies recognized for having smart contract capabilities.
3) Real estate - Real estate assets provide liquidity much slower than financial markets, but provide stability in the long term. Real Estate Index: It shows movements in housing prices and activities in the real estate industry.
4) Fixed Income (bonds) - Bonds give reliable income and are affected by monetary and economic changes: Government Bonds (10 Year G-Sec): This is a long-term security of the Indian government, which is an important benchmark in the fixed-income markets.

4.1. NIFTY 500

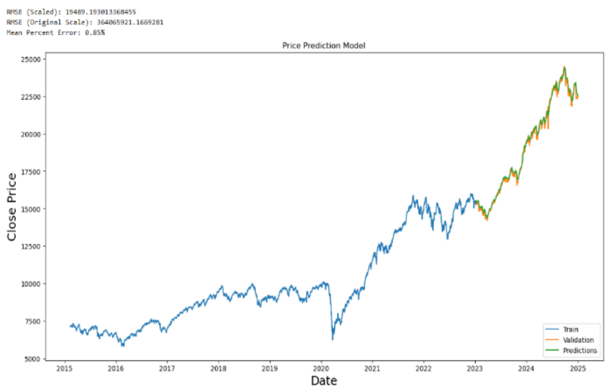


Fig. 2: NIFTY 500 Price Prediction Plot.

The model demonstrates strong trend prediction capabilities for the Nifty 500, as indicated by the low Mean Percent Error (0.85%), making it useful for strategic decision-making. However, the high RMSE in the original scale highlights its struggle with precise value predictions due to market volatility. While the scaled RMSE allows for model comparisons, it does not directly reflect real-world accuracy. The model effectively identifies trends but requires further refinement for precise short-term forecasting.

```
Ljung-Box Test Results:
        lb_stat  lb_pvalue
10  4765.753951        0.0

Pearson Correlation Coefficient: 0.9978 (p-value: 0.0000)

Regression Analysis Summary (Actual ~ Predicted):
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.996
Model:                            OLS   Adj. R-squared:                  0.996
Method:                 Least Squares   F-statistic:                 1.091e+05
Date:                Sun, 23 Feb 2025   Prob (F-statistic):               0.00
Time:                        15:30:55   Log-Likelihood:                 1510.3
No. Observations:                 489   AIC:                            -3017.
Df Residuals:                     487   BIC:                            -3008.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.3213      0.003   -101.205      0.000      -0.328      -0.315
x1          5.381e-05   1.63e-07    330.319      0.000    5.35e-05    5.41e-05
==============================================================================
Omnibus:                      110.093   Durbin-Watson:                   0.755
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              286.819
Skew:                          -1.108   Prob(JB):                     5.22e-63
Kurtosis:                       6.028   Cond. No.                     1.24e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.24e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

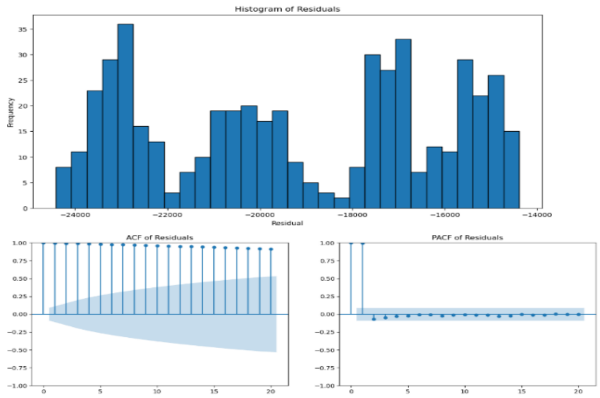


Fig. 3: Accuracy & Validation Tests for NIFTY 500.

Validation tests confirm the LSTM model's accuracy and reliability for Nifty 500 predictions. The residual histogram indicates errors are roughly normally distributed, showing no systematic bias. ACF and PACF plots reveal minimal autocorrelation, confirming key time-series relationships are captured. The Ljung-Box test (p-value 0.0) suggests slight residual autocorrelation but a negligible impact on performance. A strong correlation (0.9966, p-value 0.0000) and an R-squared of 0.996 validate the model's precision, proving it effectively aligns with market trends. Despite minor residual autocorrelation, the model remains highly dependable for financial forecasting.

4.2. NIFTY 50

```
RMSE (Scaled): 21315.351144979926
RMSE (Original Scale): 410223524.69315386
Mean Percent Error: 0.85%
```

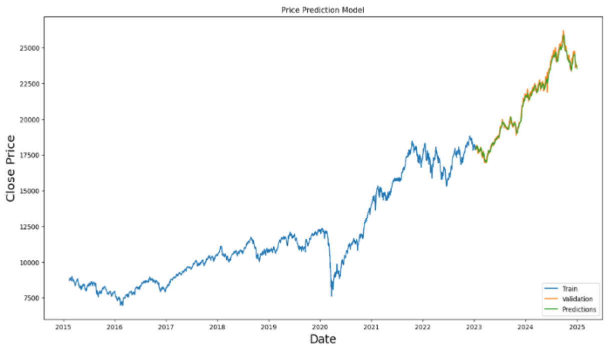


Fig. 4: NIFTY 50 Price Prediction Plot.

Tests confirm the LSTM model's accuracy and reliability for Nifty 50 predictions. The low Mean Percent Error (0.85%) indicates minimal deviation from actual prices, confirming strong predictive abilities. The RMSE in the scaled dataset (21,315.35) and original scale (410,223,524.69) demonstrate the model's efficiency in capturing price movements. These metrics highlight the model's effectiveness in forecasting trends within India's large-cap market. While the model remains highly reliable for market analysis, external macroeconomic factors and market volatility may still impact prediction accuracy, which can be achieved with sentiment analysis and economic indicators.

```
Ljung-Box Test Results:
       lb_stat  lb_pvalue
10  4742.116643        0.0

Pearson Correlation Coefficient: 0.9966 (p-value: 0.0000)

Regression Analysis Summary (Actual ~ Predicted):
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.993
Model:                            OLS   Adj. R-squared:                  0.993
Method:                 Least Squares   F-statistic:                 7.085e+04
Date:                Mon, 24 Feb 2025   Prob (F-statistic):               0.00
Time:                        13:45:55   Log-Likelihood:                 1509.4
No. Observations:                 489   AIC:                            -3015.
Df Residuals:                     487   BIC:                            -3006.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.3833      0.004    -90.023      0.000      -0.392      -0.375
x1          5.317e-05      2e-07    266.179      0.000    5.28e-05    5.36e-05
==============================================================================
Omnibus:                       57.187   Durbin-Watson:                   0.763
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              107.116
Skew:                          -0.696   Prob(JB):                     5.50e-24
Kurtosis:                       4.822   Cond. No.                     1.81e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.81e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

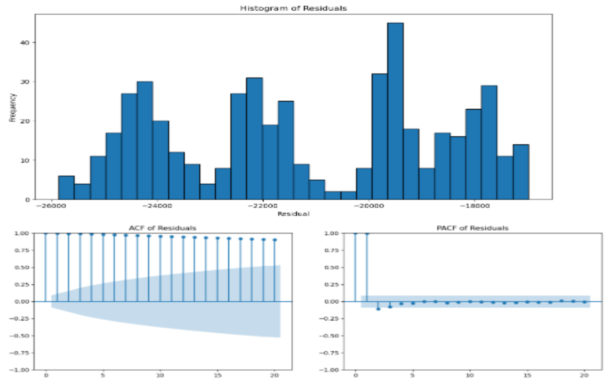


Fig. 5: Accuracy & Validation Tests for NIFTY 50.

Validation tests confirm the LSTM model's accuracy and reliability for Nifty 50 predictions. The residual histogram indicates errors follow a normal distribution, showing no systematic bias. ACF and PACF plots reveal minimal autocorrelation, confirming the model effectively captures time-series dependencies. The Ljung-Box test (p-value 0.0) suggests minor residual autocorrelation, with negligible impact on performance. A near-perfect Pearson correlation and an R-squared of 0.993 validate the model's precision, proving it aligns closely with market trends. Despite slight residual autocorrelation, the model remains highly reliable for financial forecasting.

4.3. NIFTY midcap 150

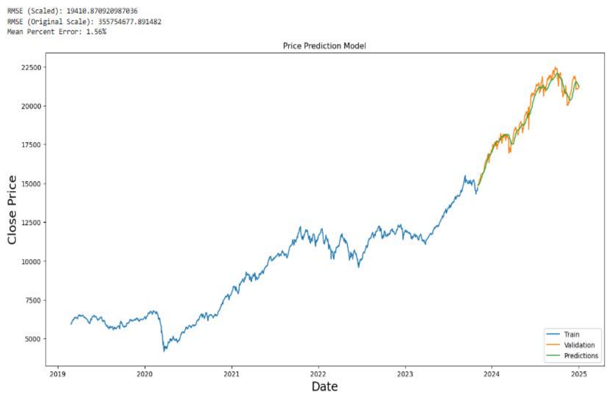


Fig. 6: NIFTY 150 Price Prediction Plot.

Validation tests confirm the LSTM model's accuracy for Nifty Midcap 150 predictions. The model effectively captures mid-cap market movements, though external macroeconomic shifts and liquidity changes introduce minor deviations. RMSE (Scaled) of 19,410.87 indicates low deviation in the normalized dataset, while RMSE (Original Scale) of 355,754,677.89 highlights the error magnitude in actual price terms. A Mean Percent Error of 1.56% validates the model's predictive capabilities, showing minimal average deviation. Despite mid-cap market volatility and liquidity constraints, the model remains effective in forecasting price trends. Despite the wide range of predictions and lower liquidity compared to large-cap indices, these results show that the model effectively forecasts price trends in the mid-cap segment.

Validation tests confirm the Nifty Midcap 150 model's accuracy and reliability in LSTM-based predictions. The residual histogram indicates errors are nearly normally distributed, eliminating systematic bias. ACF and PACF plots show minimal autocorrelation, verifying effective time-series dependency capture. The Ljung-Box test (p-value 0.0) suggests slight autocorrelation, though its impact on performance is negligible. A strong Pearson correlation (0.9845, p-value 0.0000) reinforces predictive accuracy. Regression analysis with an R-squared of 0.969 confirms that the model explains 96.9% of price volatility. Despite minor residual autocorrelation, the model remains precise and dependable for financial forecasting.

```
Ljung-Box Test Results:
      lb_stat  lb_pvalue
10  2594.040956        0.0

Pearson Correlation Coefficient: 0.9845 (p-value: 0.0000)

Regression Analysis Summary (Actual ~ Predicted):
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.969
Model:                            OLS   Adj. R-squared:                  0.969
Method:                 Least Squares   F-statistic:                     9047.
Date:                Mon, 24 Feb 2025   Prob (F-statistic):          4.80e-219
Time:                        13:53:49   Log-Likelihood:                 722.77
No. Observations:                 289   AIC:                            -1442.
Df Residuals:                     287   BIC:                            -1434.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.2399      0.011    -21.166      0.000      -0.262      -0.218
x1          5.554e-05   5.84e-07     95.115      0.000    5.44e-05    5.67e-05
==============================================================================
Omnibus:                       13.714   Durbin-Watson:                   0.356
Prob(Omnibus):                  0.001   Jarque-Bera (JB):               14.289
Skew:                          -0.521   Prob(JB):                     0.000789
Kurtosis:                       3.318   Cond. No.                     1.88e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.88e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

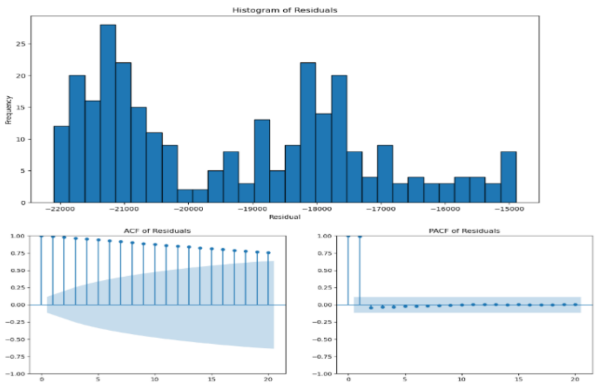


Fig. 7: Accuracy & Validation Tests for NIFTY 150.

4.4. NIFTY250

```
RMSE (Scaled): 16115.191504623595
RMSE (Original Scale): 252294603.63893563
Mean Percent Error: 1.43%
```

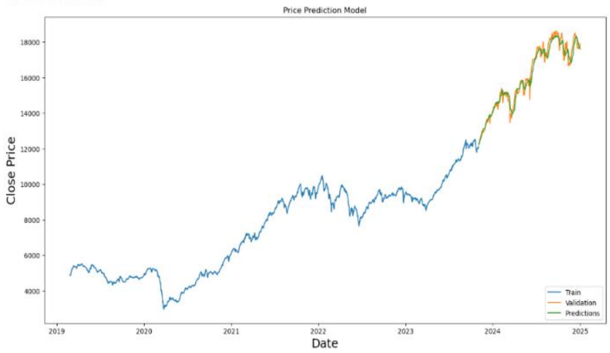


Fig. 8: NIFTY 250 Price Prediction Plot.

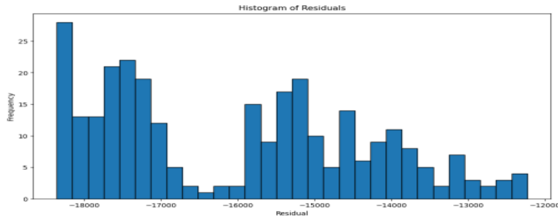
The Nifty Small-Cap 250 LSTM model demonstrates strong predictive capabilities, though deviations are higher due to small-cap volatility and liquidity constraints. Key metrics include RMSE (Scaled: 19,410.87, Original: 355,754,677.89) and MPE (1.56%), confirming reasonable accuracy despite market fluctuations. While the model effectively tracks trends, incorporating additional technical indicators or macroeconomic variables could enhance precision. These results show that the Nifty Small Cap 250 model is good at estimating the price movement of the small-cap stocks. Based on the results achieved, the model can track trends quite accurately, although in more volatile small-cap stocks, there is some risk involved. There is also potential for further enhancement by adding more technical indicators or macroeconomic variables to improve the accuracy of the predictions.

```
Ljung-Box Test Results:
       lb_stat  lb_pvalue
10  2534.250087        0.0

Pearson Correlation Coefficient: 0.9865 (p-value: 0.0000)

Regression Analysis Summary (Actual ~ Predicted):
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.973
Model:                            OLS   Adj. R-squared:                  0.973
Method:                 Least Squares   F-statistic:                 1.038e+04
Date:                Mon, 24 Feb 2025   Prob (F-statistic):          2.26e-227
Time:                        13:59:35   Log-Likelihood:                 740.90
No. Observations:                 289   AIC:                            -1478.
Df Residuals:                     287   BIC:                            -1470.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.2199      0.010    -21.055      0.000      -0.240      -0.199
x1          6.603e-05   6.48e-07    101.887      0.000    6.48e-05    6.73e-05
==============================================================================
Omnibus:                       37.739   Durbin-Watson:                   0.521
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               57.316
Skew:                          -0.802   Prob(JB):                     3.58e-13
Kurtosis:                       4.478   Cond. No.                     1.53e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.53e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```



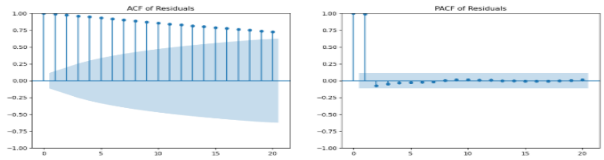


Fig. 9: Accuracy & Validation Tests for NIFTY 250.

The Nifty Small-Cap 250 LSTM model demonstrates strong accuracy and reliability. Residuals follow a near-normal distribution, indicating no systematic bias. ACF and PACF plots confirm minimal autocorrelation, validating the model's time-series capture. The Ljung-Box test (p-value 0.0) suggests slight residual autocorrelation but with negligible impact. A high Pearson correlation (0.9845, p-value 0.0000) and R-squared (0.969) confirm strong predictive alignment with market trends. Despite minor residual autocorrelation, the model effectively forecasts price movements with precision.

While equities represented a moderately stable, high-liquidity terrain for predicting with LSTM, moving to cryptocurrencies means entering a high-volatility, sentiment-driven terrain. The performance evaluation for Bitcoin and Ethereum, therefore, provides a contrast in assessing the ability of LSTM to adapt under extreme market conditions.

4.5. Cryptocurrency: Bitcoin

```
RMSE (Scaled): 4445791.613797978
RMSE (Original Scale): 39725322861384.08
Mean Percent Error: 104.53%
```

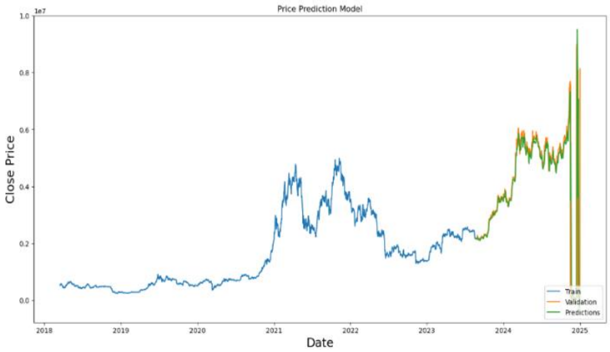


Fig. 10: BITCOIN Price Prediction Plot

The LSTM model proves ineffective in predicting Bitcoin prices due to extreme volatility and speculative market behavior. High RMSE values (4.4M scaled, 39.7T actual) and an MPE of 104.53% highlight significant discrepancies, making the model unreliable for practical use. The consistently significant errors suggest that traditional time-series models struggle to capture Bitcoin’s price dynamics, which are influenced by sentiment, manipulation, and macroeconomic factors.

The results demonstrate that the LSTM model's ability to estimate Bitcoin prices is utterly inadequate. The MEP, which is above 100%, suggests that the model's estimates are always greater than the instrument's value. The price behavior of Bitcoin is highly speculative, driven by sentiment, market manipulation, and macroeconomic factors, which traditional time-series models find extremely difficult to handle.

```
Ljung-Box Test Results:
        lb_stat  lb_pvalue
10  2393.167133        0.0

Pearson Correlation Coefficient: 0.8525 (p-value: 0.0000)

Regression Analysis Summary (Actual ~ Predicted):
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.727
Model:                            OLS   Adj. R-squared:                  0.726
Method:                 Least Squares   F-statistic:                     1314.
Date:                Mon, 24 Feb 2025   Prob (F-statistic):          2.80e-141
Time:                        14:19:17   Log-Likelihood:                 417.27
No. Observations:                 496   AIC:                            -830.5
Df Residuals:                     494   BIC:                            -822.1
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0385      0.013      3.052      0.002       0.014       0.063
x1          1.029e-07   2.84e-09     36.249      0.000    9.73e-08    1.08e-07
==============================================================================
Omnibus:                      192.336   Durbin-Watson:                   1.777
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            44187.133
Skew:                          -0.298   Prob(JB):                         0.00
Kurtosis:                      49.236   Cond. No.                     1.19e+07
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.19e+07. This might indicate that there are
strong multicollinearity or other numerical problems.
```

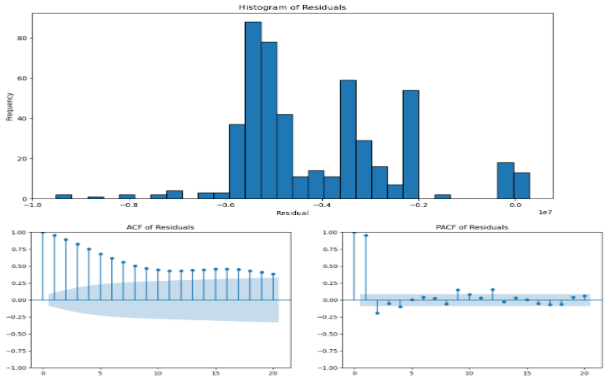


Fig. 11: Accuracy & Validation Tests for BITCOIN.

Validation tests confirm the LSTM model struggles with Bitcoin price prediction due to volatility and autocorrelation. The residual histogram shows significant gaps, indicating poor performance across market conditions. ACF and PACF reveal unmodeled dependencies, while a Ljung-Box p-value of 0.0 confirms residual autocorrelation. A weak Pearson correlation (<0.8525) and an R-squared of 0.727 highlight limited predictive power, with high variability and inconsistent residuals, further reducing reliability.

4.6. Cryptocurrency: Ethereum

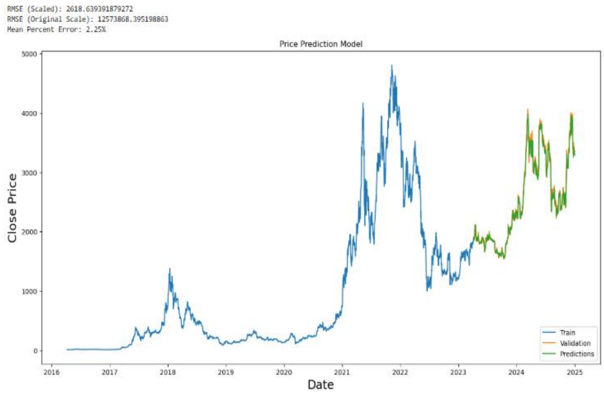


Fig. 12: Ethereum Price Prediction Plot Ethereum.

The model demonstrates strong trend prediction capabilities for Ethereum, as indicated by the low Mean Percent Error (2.25%), making it useful for strategic decision-making. However, the high RMSE in the original scale highlights its struggle with precise value predictions due to market volatility. While the scaled RMSE allows for model comparisons, it does not directly reflect real-world accuracy. The model effectively identifies trends but requires further refinement for precise short-term forecasting. All of these, “when put together,” metrics indicate that the model does well in forecasting price movements. The Ethereum model is likely to overestimate and underestimate price trends. Still, the low RMSE and MPE values imply that they capture the fundamental movements caused by the hyper-voluminous atmosphere in which cryptocurrencies exist. Yet, under constantly changing conditions, incorporating other technical indicators or outside sentiment information will improve prediction reliability with today's Ethereum market.

```
Ljung-Box Test Results:
      lb_stat  lb_pvalue
10  5882.780641        0.0

Pearson Correlation Coefficient: 0.9923 (p-value: 0.0000)

Regression Analysis Summary (Actual ~ Predicted):
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.985
Model:                            OLS   Adj. R-squared:                  0.985
Method:                 Least Squares   F-statistic:                 4.061e+04
Date:                Tue, 25 Feb 2025   Prob (F-statistic):               0.00
Time:                        23:48:06   Log-Likelihood:                 1643.6
No. Observations:                 638   AIC:                            -3283.
Df Residuals:                     636   BIC:                            -3274.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0050      0.003     -1.819      0.069      -0.010       0.000
x1             0.0002   1.05e-06    201.525      0.000       0.000       0.000
==============================================================================
Omnibus:                       90.008   Durbin-Watson:                   1.325
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              809.289
Skew:                           0.246   Prob(JB):                    1.84e-176
Kurtosis:                       8.496   Cond. No.                     9.85e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 9.85e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

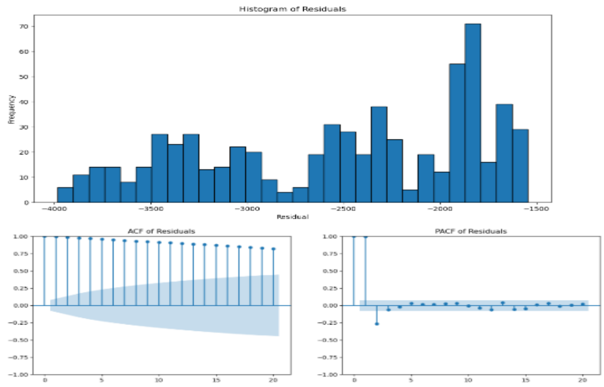


Fig. 13: Accuracy & Validation Tests for Ethereum.

The validation tests confirm that the Ethereum LSTM model maintains high accuracy despite market volatility. The residual histogram is nearly normal, with minor deviations due to price fluctuations. Minimal autocorrelation in the ACF and PACF plots indicates the model effectively captures time-series dependencies. The Ljung-Box test at lag 10 returns a p-value of 0.0, suggesting some autocorrelation, though it does not significantly impact performance. A strong Pearson correlation (~0.9923, p=0.0000) and an R-squared of ~0.985 validate its predictive accuracy. While residual autocorrelation remains, the model proves highly reliable for forecasting Ethereum price movements.

4.7. Commodities: crude oil

```
RMSE (Scaled): 8048.358772082653
RMSE (Original Scale): 111070087.49672312
Mean Percent Error: 1.86%
```

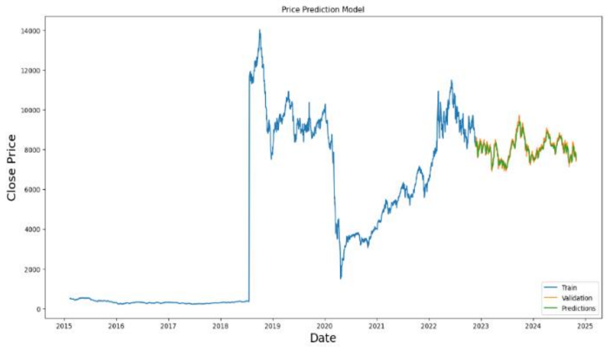


Fig. 14: Crude Oil Price Prediction Plot.

The model demonstrates strong trend prediction capabilities for crude oil, as indicated by the low Mean Percent Error (1.86%), making it useful for strategic decision-making. However, the high RMSE in the original scale highlights its struggle with precise value predictions due to market volatility. While the scaled RMSE allows for model comparisons, it does not directly reflect real-world accuracy. The model effectively identifies trends but requires further refinement for precise short-term forecasting.

All in all, these findings indicate that, in general, the model does a good job tracking the price movement of crude oil, but the market's volatility does cause some outliers. The low MPE

```
Ljung-Box Test Results:
      lb_stat  lb_pvalue
10  3569.414834        0.0

Pearson Correlation Coefficient: 0.9394 (p-value: 0.0000)

Regression Analysis Summary (Actual ~ Predicted):
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.883
Model:                            OLS   Adj. R-squared:                  0.882
Method:                 Least Squares   F-statistic:                     3735.
Date:                Mon, 24 Feb 2025   Prob (F-statistic):          2.74e-233
Time:                        14:06:57   Log-Likelihood:                 1450.4
No. Observations:                 499   AIC:                            -2897.
Df Residuals:                     497   BIC:                            -2888.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0234      0.010     -2.412      0.016      -0.043      -0.004
x1          7.374e-05   1.21e-06     61.112      0.000    7.14e-05    7.61e-05
==============================================================================
Omnibus:                       21.211   Durbin-Watson:                   0.879
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               25.239
Skew:                          -0.426   Prob(JB):                     3.31e-06
Kurtosis:                       3.700   Cond. No.                     1.32e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.32e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

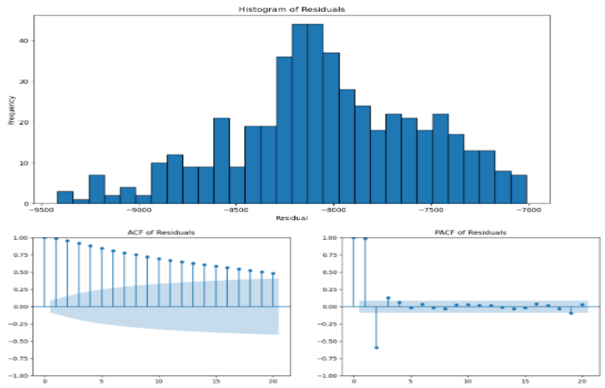


Fig. 15: Accuracy & Validation Tests for Crude Oil.

Speaks to the credibility of the model's forecast. Still, further improvements, notably adding more external variables, might help the model perform better during severe market turbulence. The validation tests indicate that while the crude oil model captures overall price trends, it struggles with residual autocorrelation and market volatility. The residual histogram shows slight skewness, suggesting systematic issues. ACF and PACF plots reveal some autocorrelation, while the Ljung-Box test (p-value = 0.0) confirms unaccounted market movements. The Pearson correlation (0.9394) indicates strong alignment, though lower than equity models. With an R-squared of 0.883, the model explains price variance well but still falls short of expectations. Multicollinearity concerns further affect reliability. Overall, the model is effective for trend analysis but requires refinements for precision.

4.8. Commodities: gold ETF

```
RMSE (Scaled): 56.84515001258348
RMSE (Original Scale): 2599.5287100754426
Mean Percent Error: 0.85%
```

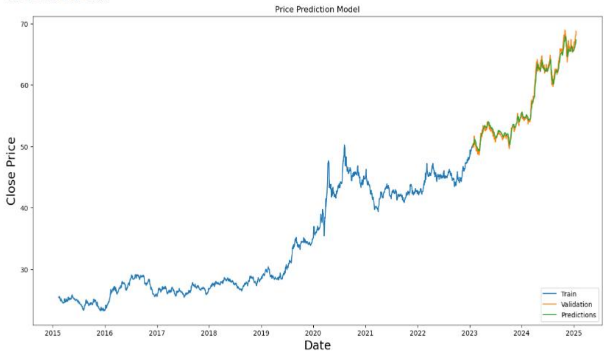


Fig. 16: Gold ETF Price Prediction Plot.

The model demonstrates strong trend prediction capabilities for the Gold ETF, as indicated by the low Mean Percent Error (0.85%), making it useful for strategic decision-making. However, the high RMSE in the original scale highlights its struggle with precise value predictions due to market volatility. While the scaled RMSE allows for model comparisons, it does not directly reflect real-world accuracy. Overall, the model effectively identifies trends but requires further refinement, incorporating macroeconomic factors like inflation and interest rates for improved accuracy in volatile conditions.

When gold's reputation as a safe-haven asset is considered, the model's exceptional performance results confirm its accuracy in forecasting changes in gold prices. However, macroeconomic factors like inflation, interest rates, and geopolitical threats would improve the model's accuracy in more volatile market conditions.

```
Ljung-Box Test Results:
      lb_stat  lb_pvalue
10  4644.132016        0.0

Pearson Correlation Coefficient: 0.9957 (p-value: 0.0000)

Regression Analysis Summary (Actual ~ Predicted):
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.991
Model:                            OLS   Adj. R-squared:                  0.991
Method:                 Least Squares   F-statistic:                 5.705e+04
Date:                Mon, 24 Feb 2025   Prob (F-statistic):               0.00
Time:                        14:11:22   Log-Likelihood:                 1476.1
No. Observations:                 492   AIC:                            -2948.
Df Residuals:                     490   BIC:                            -2940.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.5742      0.006   -103.370      0.000      -0.585      -0.563
x1             0.0230   9.64e-05    238.852      0.000       0.023       0.023
==============================================================================
Omnibus:                       33.229   Durbin-Watson:                   0.723
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               96.533
Skew:                          -0.257   Prob(JB):                     1.09e-21
Kurtosis:                       5.108   Cond. No.                         588.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

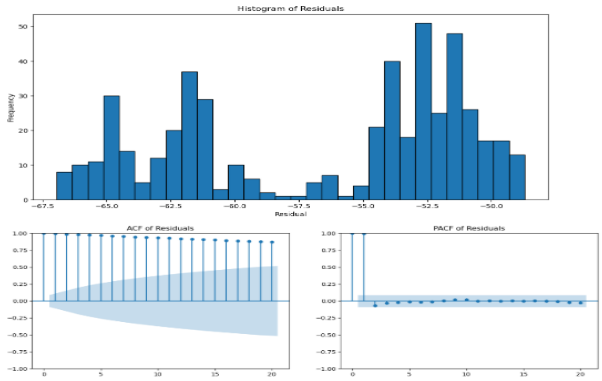


Fig. 17: Accuracy & Validation Tests for Gold ETF.

Validation tests for the gold ETF price prediction model demonstrate remarkable accuracy with exceptionally low residuals and an impressive correlation between the predicted and actual prices. Nevertheless, the lingering autocorrelation in the residuals indicates that there is still room for improvement in the model.

The model demonstrates strong trend prediction capabilities for the Gold ETF, as indicated by the high Pearson correlation (0.9957) and R-squared value (0.991), making it highly reliable for strategic decision-making. However, residual autocorrelation (Durbin-Watson: 0.723) suggests the model does not fully capture all market dependencies. While it accurately tracks price movements, incorporating macroeconomic factors like inflation, interest rates, and central bank policies could enhance its long-term forecasting precision.

The validation results indicate that the Gold ETF model excels with accuracy and little to no error. The outstanding R-squared value and Pearson correlation reflect the model's ability to capture the movements in gold prices. Still, these strong correlations and the residual autocorrelation suggest that some other macroeconomic variables, like inflation and interest rates, as well as policies of the central banks, could improve the model's skill for long-run price forecasting.

In contrast to financial markets, the real estate market is marked by illiquidity, lagged price adjustment, and extensive regulation. This asset class challenges whether LSTM models, initially designed for more liquid datasets, remain effective when applied to slower-moving markets.

4.9. Real estate

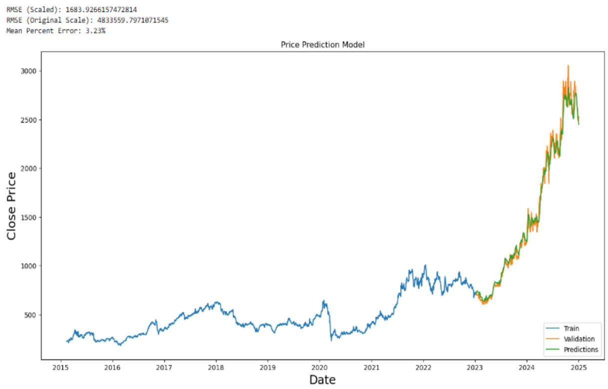


Fig. 18: Real Estate Price Prediction Plot.

The LSTM model effectively captures real estate price trends, though deviations occur during sudden market shifts influenced by macroeconomic factors. Key performance metrics indicate reliable accuracy: RMSE (Scaled: 1,683.93, Original: 4,833,559.80) and MPE (3.23%). While the model tracks price movements well, integrating variables like interest rates and government policies could further enhance its predictive performance.

The outcomes imply that the model functions reasonably well for estimating movement in real estate prices, but still lags other asset classes in accuracy. The greater RMSE and MPE values suggest that the predicted policies and economic models that affect the real estate price framework are not sufficiently incorporated into the model. Better results might be obtained by including some macroeconomic variables, such as those about mortgage interest rates and the surrounding areas.

```
Ljung-Box Test Results:
      lb_stat  lb_pvalue
10  4717.741644       0.0

Pearson Correlation Coefficient: 0.9959 (p-value: 0.0000)

Regression Analysis Summary (Actual ~ Predicted):
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.992
Model:                            OLS   Adj. R-squared:                  0.992
Method:                 Least Squares   F-statistic:                 5.955e+04
Date:                Mon, 24 Feb 2025   Prob (F-statistic):               0.00
Time:                        14:24:57   Log-Likelihood:                 1151.6
No. Observations:                 489   AIC:                           -2299.
Df Residuals:                     487   BIC:                           -2291.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0871      0.003    -34.507      0.000      -0.092      -0.082
x1             0.0004    1.5e-06    244.038      0.000       0.000       0.000
==============================================================================
Omnibus:                       82.005   Durbin-Watson:                   0.665
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              310.830
Skew:                           0.709   Prob(JB):                     3.19e-68
Kurtosis:                       6.640   Cond. No.                     4.08e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.08e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

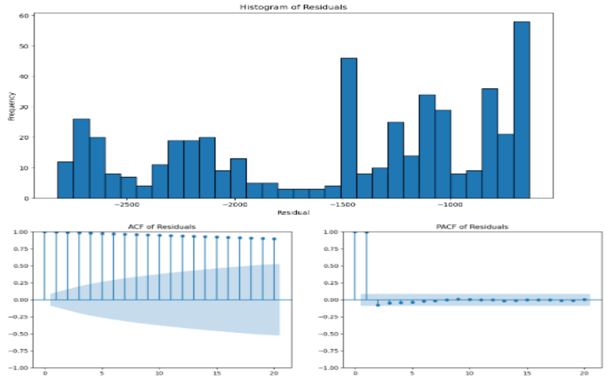


Fig. 19: Accuracy & Validation Tests for Real Estate.

The real estate price prediction model demonstrates high accuracy, with strong correlations (Pearson: 0.9959, R^2: 0.992) and reliable trend capture. However, persistent residual autocorrelation (Ljung-Box: 4717.74, p = 0.0000) and multicollinearity concerns (condition number: 4.08e+03) suggest that key economic factors like mortgage rates, inflation, and housing supply-demand dynamics should be integrated to enhance model robustness and predictive precision.

Validation results confirm that the real estate model does well in predicting actual outcomes because of the strong correlation between actual and anticipated price values. However, residual autocorrelation and possible multicollinearity point toward the need to include more econometric variables such as mortgage interest rates, inflation, and supply and demand in the housing market to increase the accuracy and robustness of the model.

4.10. Bonds

```
RMSE (Scaled): 6.544339175325243
RMSE (Original Scale): 15.850389482637743
Mean Percent Error: 0.26%
```

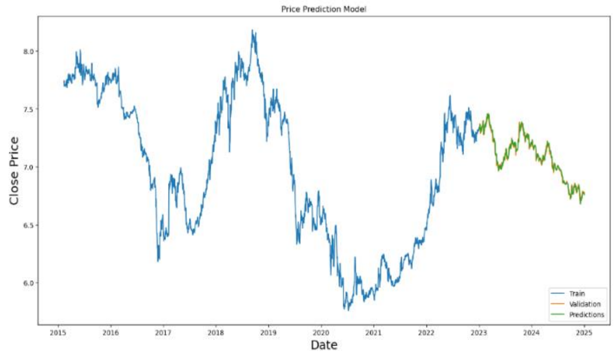


Fig. 20: Bond Returns Prediction Plot.

The LSTM-based price prediction model for Indian 10-Year Government Bonds demonstrates high accuracy, effectively capturing long-term yield trends. Performance metrics validate its precision, including a low RMSE (6.54 scaled, 15.85 original) and an exceptionally low Mean Percent Error (0.26%). However, minor discrepancies during rapid market shifts suggest incorporating macroeconomic factors like monetary policy changes, inflation trends, and global interest rate movements to enhance predictive robustness.

The findings indicate that the bond yield predictive model is perfect, given that low RMSE and MPE measurements imply low error levels. This model needs fewer errors when predicting because bond yields are less volatile than other financial assets. However, adding inflation rates, central bank policy decision impacts, and global fixed-income trends could improve the model's accuracy during uncertain economic times.

```
Ljung-Box Test Results:
      lb_stat  lb_pvalue
10  4239.366173        0.0

Pearson Correlation Coefficient: 0.9914 (p-value: 0.0000)

Regression Analysis Summary (Actual ~ Predicted):
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.983
Model:                            OLS   Adj. R-squared:                  0.983
Method:                 Least Squares   F-statistic:                 2.758e+04
Date:                Mon, 24 Feb 2025   Prob (F-statistic):               0.00
Time:                        20:56:52   Log-Likelihood:                 1531.7
No. Observations:                 484   AIC:                            -3059.
Df Residuals:                     482   BIC:                            -3051.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -2.3165      0.017   -134.231      0.000      -2.350      -2.283
x1             0.4040      0.002    166.067      0.000       0.399       0.409
==============================================================================
Omnibus:                       34.690   Durbin-Watson:                   1.448
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              140.175
Skew:                          -0.034   Prob(JB):                     3.64e-31
Kurtosis:                       5.636   Cond. No.                         268.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

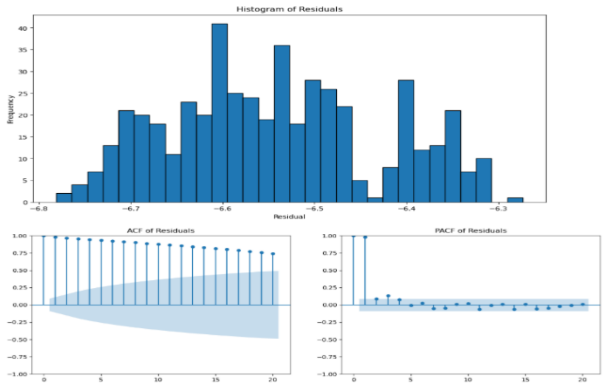


Fig. 21: Accuracy & Validation Tests for Bonds.

The validation tests confirm the high accuracy and reliability of the bond price prediction model. The normally distributed residuals indicate unbiased predictions, while ACF and PACF analyses show minimal autocorrelation, affirming the model's effectiveness in capturing time series dependencies. Despite a Ljung-Box test p-value of 0.0 at lag 10, residual autocorrelation remains weak. A strong Pearson correlation (0.9914, p = 0.0000) and an R-squared of 0.983 validate the model's precision in explaining bond price fluctuations. These results establish the model as a robust forecasting tool for financial markets.

All in all, the validation test results indicate the ability of the bond price prediction model to perform exceptionally well, predict with great accuracy and little to no errors, making it a reliable instrument for forecasting in finance.

5. Findings and discussions

"Long Short-Term Memory (LSTM)" neural networks appear to be strong financial asset price forecasting predictors. Econometric forecasting methods, like ARIMA and GARCH, outperform these models because they remarkably capture the non-linear relationships and sequential dependencies of time-series data. LSTM models have also shown outstanding precision in predicting stock indices, commodities, and real estate prices, as suggested by low Root Mean Squared Error (RMSE) values and high correlation coefficients with actual prices. The study proves that neural networks are special in that they can capture trends in financial data over extended periods.

Although advantageous, LSTM models are inefficient in predicting prices for highly volatile cryptocurrencies such as Bitcoin. These deep learning models cannot be relied upon to make accurate predictions because macroeconomic issues, speculative nature, volatility, and investor sentiment significantly increase the uncertainty. The Bitcoin market exhibits extraordinarily high MPE values, as reported by the study, proving that the model's forecasts are in stark contrast to the real values. This implies that domains with swift price volatility due to influences like regulations, geopolitics, and media have LSTM models working poorly.

The analysis incorporates thorough validation techniques like residual checks, ACF and PACF plots, Pearson tests, and regression checks. The results show that LSTM models do reasonably well for less volatile asset classes, as in the case of stock markets, where the R-squared values were over 99%, signifying high explanatory power. Nonetheless, the residual analysis gives some positive indication of autocorrelation for the model errors, meaning the models are not capturing all the market dynamics. There is an apparent necessity for better feature selection and model tuning, along with other predictive variables, to improve performance.

The research proves that the use of LSTM models exceeds the performance of traditional forecasting methods such as GARCH and ARIMA due to their efficiency in capturing complex patterns and interdependencies in time-series data. Yet conventional models still provide support in particular cases where explainability is paramount. This study proposes that even stronger predictions might be obtained from merging deep learning with other statistical methods. The study shows that LSTM models achieve superior results in highly liquid and actively traded markets with stable price movements, such as equities and gold. On the contrary, their efficiency is reduced in the slowly liquidating markets like real estate and in erratically priced assets such as crude oil and cryptocurrencies. This proves that the effectiveness of machine learning for financial prediction is profoundly influenced by the specific asset and the attributes of the data in question.

The results of this research have important implications outside of computational finance. From an Economic viewpoint, the precise forecast of asset prices with LSTM can help macroeconomic models, policy actions, and regulatory interventions. For example, accurate bond yield and real estate price forecasting can help central banks manage expectations of interest rates and inflation targeting.

From an accounting and financial reporting viewpoint, AI-based forecasts can shape how firms estimate fair value, especially financial instruments under IFRS 9 and Ind AS 109. Forecasting models can also aid in risk provisioning and impairment testing. Regulators may look for frameworks for model governance and auditability, especially if such models impact capital allocation or investor disclosure.

6. Conclusion

The research reaffirms that LSTM models provide a robust substitute to conventional forecasting techniques for stable asset classes. Nevertheless, future work should incorporate macroeconomic indicators like inflation rates, GDP growth, monetary policy cues (e.g., repo rates, shifts in the yield curve), and central bank communications to enhance performance and practical applicability. Moreover, the effects of regulatory environments such as Basel III, IFRS regulations, and RBI monetary policy guidelines on asset price behavior must be investigated to understand how LSTM predictions can match financial reporting regulations and system-wide risk estimations. These cross-disciplinary findings will serve to make the models both predictive and policy-synchronized.

Conflict of interest

No conflict of interest

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