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A Data-Driven Deep Sequential Learning Approach for Digital Financial Asset Price Prediction Using LSTM Networks

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Abstract—**The prediction of digital financial asset prices has become a challenging task due to the highly volatile and non-linear nature of modern financial markets. Traditional statistical and machine learning models often struggle to capture complex temporal dependencies present in financial time-series data. This study proposes a data-driven deep sequential learning approach for digital financial asset price prediction using Long Short-Term Memory (LSTM) networks. The proposed framework learns temporal patterns directly from historical market data without relying on predefined rules or assumptions.**

In this work, Bitcoin is considered as a representative digital financial asset due to its high liquidity and availability of long-term historical data. Daily Open, High, Low, and Close (OHLC) price data spanning from 2019 to 2025 is utilized for model training and evaluation. To establish a performance baseline, a Random Forest regression model is implemented and compared with the proposed LSTM-based approach. The models are evaluated using standard performance metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). Experimental results demonstrate that the LSTM model significantly outperforms the Random Forest model by effectively capturing long-term temporal dependencies in the price series. The proposed deep sequential learning framework achieves higher prediction accuracy and better generalization capability, making it suitable for digital financial market analysis and decision-support applications. The findings highlight the effectiveness of deep learning-based sequential models for price forecasting in highly volatile digital asset markets.

Index Terms—**Digital Assets managements, Bitcoin Price Prediction, LSTM Networks, Random Forest Regressor, Time Series Forecasting, Deep Learning, Cryptocurrency Market**

I. INTRODUCTION

The prediction of digital financial asset prices has gained increasing relevance… Bitcoin, as a leading digital asset, is considered in this study as a representative case. Bitcoin, a decentralized digital currency, presents unique challenges in forecasting due to its susceptibility to rapid and unpredictable market fluctuations influenced by macroeconomic events, sentiment, and speculation. Traditional statistical models fall short in capturing the complex nonlinear patterns and long-term dependencies embedded in such financial time series.

This study introduces a hybrid deep learning-based methodology that leverages real-time data sourced from Yahoo Finance APIs spanning a six-year period (2019–2025). We integrate an LSTM-based architecture, known for its temporal memory capabilities, with ensemble methods like Random Forest to evaluate their respective forecasting performances. Our goal is to identify an accurate and scalable model for Bitcoin price prediction that can adapt to real-time data streams and provide actionable financial insights.

We also compare the models on the basis of performance metrics such as RMSE, MAE, and R^2 score. The integration of real-time data acquisition and automated visualization further enhances the practical usability of the system in financial applications and investment forecasting.

II. LITERATURE REVIEW

Numerous studies have explored cryptocurrency prediction using both machine learning and deep learning models. Patel et al. (2015) utilized SVM, ANN, and Random Forest for Indian stock market forecasting, indicating the potential of ensemble learning in financial prediction. McNally et al. (2018) applied LSTM networks for Bitcoin prediction, revealing their superiority in capturing long-term dependencies.

Karale and Sable (2020) extended this idea by comparing ARIMA with LSTM models, showing deep learning's edge in non-linear series modeling. In [1], Chen et al. explored hybrid deep learning models for predicting high-frequency trading data. Gupta and Garg (2022) proposed a CNN-LSTM hybrid for enhanced time-series prediction in cryptocurrency.

Other approaches have incorporated sentiment analysis ([2], [3]) and cloud-computing-based architectures ([4]) for scalability. However, few have addressed integration with real-time APIs like Yahoo Finance, CoinGecko, and Binance for on-demand forecasting, which this paper aims to fill.

III. PROPOSED METHODOLOGY

Although the proposed framework is applicable to a wide range of digital financial assets, Bitcoin is used as a representative dataset due to its high liquidity and data availability. our proposed system includes the following key components:

- Data Acquisition Layer: Real-time Bitcoin price data fetched using yfinance from Yahoo Finance covering the period from June 2019 to June 2025.
- Data Preprocessing: MinMax scaling, missing value treatment, time series window slicing.
- Modeling Layer: Sequential LSTM network and Random Forest model.
- Prediction & Evaluation: Prediction for unseen data, comparison via RMSE, MAE, R^2 metrics.
- Visualization Layer: Dynamic plotting of predicted vs actual values.

3.1 Data Collection

We used the yfinance API to fetch historical Bitcoin OHLC data from June 11, 2019 to June 11, 2025. The dataset includes Open, High, Low, and Close prices which are critical for understanding market behavior.

```
df = yf.download("BTC-USD", start="2019-06-11", end="2025-06-11")
df = df[['Open', 'High', 'Low', 'Close']]
```

3.2 Data Preprocessing and Feature Scaling

The input features were scaled to the [0,1] range using Min-Max normalization, which helps LSTM converge faster during training:

$$\frac{X' = X - Xmin}{Xmax - Xmin}$$

Where:

- X is the original value
- X′ is the normalized value
- Xmin, Xmax are the minimum and maximum values of the feature

We used a sliding window of 60-time steps to predict the 61st price:

Sequence=$\{Pt - 60, Pt - 59, \ldots, Pt - 1\} \Rightarrow Pt$

3.3 LSTM Model Architecture

The LSTM model captures long-term dependencies by using gated recurrent units:

- Forget Gate:

$$ft = \sigma(Wf \cdot [ht - 1, xt] + bf)$$

- Input Gate:

$$it = \sigma(Wi \cdot [ht - 1, xt] + bi)$$
$$C{\sim}t = \tanh(WC \cdot [ht - 1, xt] + bC)$$

- Cell State Update:

$$Ct = ft \cdot Ct - 1 + it \cdot C{\sim}t$$

- Output Gate:

$$ot = \sigma(Wo \cdot [ht - 1, xt] + bo)$$
$$ht = ot \cdot \tanh(Ct)$$

Where:

- xi: input at time t
- hth_: hidden state at time t
- Ct: cell state at time t
- σ: sigmoid activation
- W: weights and biases

The final output layer was a fully connected Dense layer:$\mathrm{model.add(Dense(1))}$

3.4 Random Forest Model

Random Forest is an ensemble learning technique that averages predictions from multiple decision trees:

ŷ = (1/n) * Σ T_i(x)

Where:

- y^: final prediction
- Ti(x) prediction from the i-th decision tree

We trained RF using the same feature-target pairs as LSTM but without temporal dependencies.

3.5 Performance Metrics

We evaluated the models using three core metrics:

- Root Mean Square Error (RMSE)

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

Mean Absolute Error (MAE)

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

- Coefficient of Determination (R^2 Score)

$$R^2 = 1 - [\Sigma(y\_i - \hat{y}\_i)^2 / \Sigma(y\_i - \bar{y})^2]$$

Where:

- yi: actual value
- y^i: predicted value
- y¯: mean of actual values

IV. RESULTS AND DISCUSSION

4.1 Performance Comparison

Model	RMSE	MAE	R^2 Score
LSTM	2967.35	2213.65	0.9517
Random Forest	8153.58	4269.55	0.6351

Table 1. Performance Comparison

4.2 Observations:

LSTM showed excellent performance in capturing temporal dependencies. Random Forest had higher error margins and underperformed on trend prediction. Real-time prediction matched expected price movements during volatile periods.

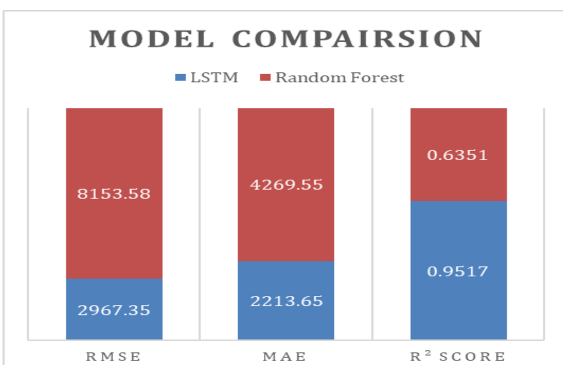

figure 1. Performance Comparison

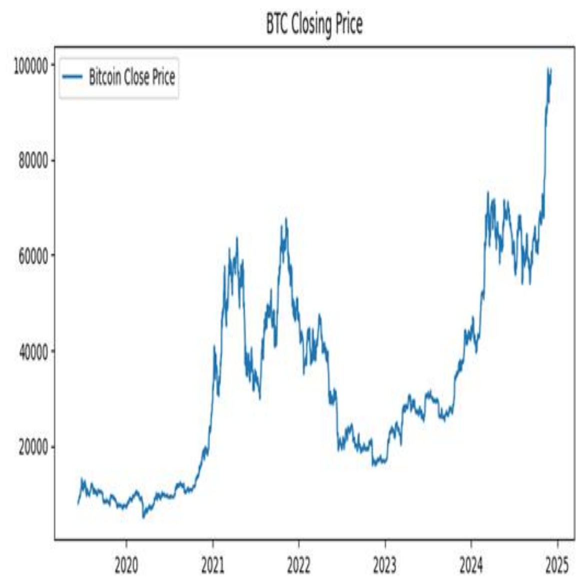

figure 2. BTC closing price

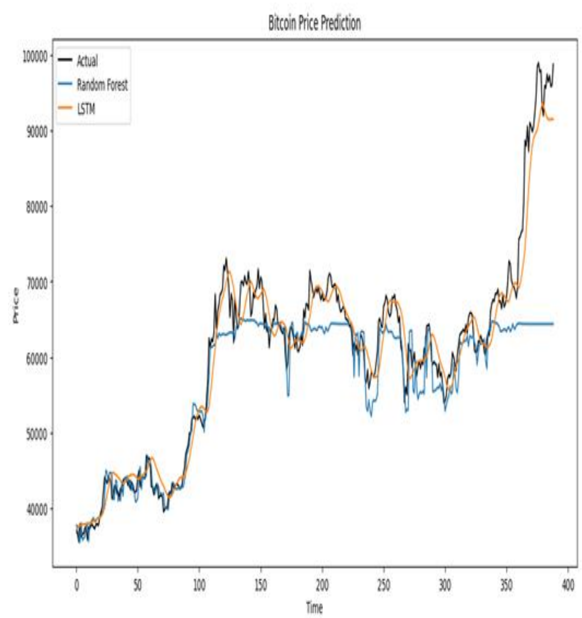

figure 3. BTC price prediction actual vs RF vs LSTM

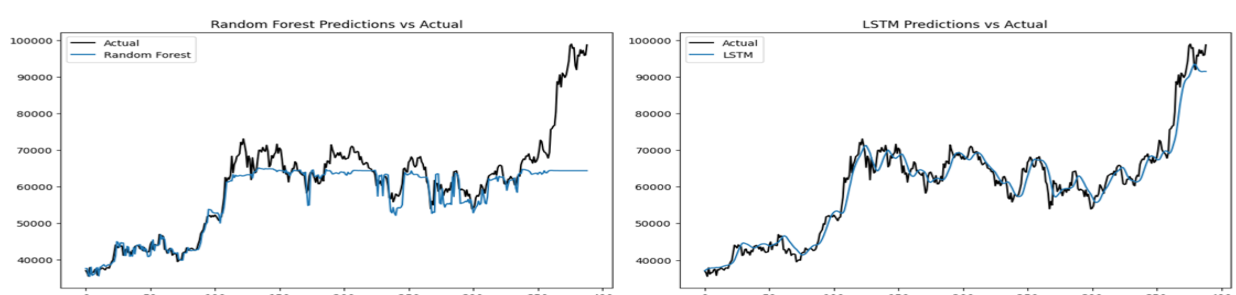

figure 3. BTC price prediction comparison graph actual and RF vs actual and LSTM

V. CONCLUSION

This study presented a data-driven deep sequential learning framework for digital financial asset price prediction, with Bitcoin used as a representative case due to its liquidity and availability of historical data. By leveraging Long Short-Term Memory (LSTM) networks, the proposed approach effectively modeled the temporal dependencies inherent in financial time-series data, which are often difficult to capture using traditional machine learning techniques.

A comparative analysis was conducted between a Random Forest regression model and the LSTM-based deep learning model using daily OHLC price data from 2019 to 2025. The evaluation, based on RMSE, MAE, and R^2 metrics, demonstrated that the LSTM model consistently outperformed the Random Forest baseline. This performance improvement highlights the capability of deep sequential learning models to capture long-term patterns and non-linear market dynamics more accurately than ensemble-based machine learning methods.

The findings of this research confirm that deep learning approaches, particularly LSTM networks, provide a robust and reliable solution for digital financial asset price forecasting. The proposed framework is not limited to a single asset and can be extended to other digital financial instruments with similar time-series characteristics. Overall, this study contributes a scalable and effective predictive framework that can support intelligent decision-making and analytical applications in modern digital financial markets.

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