

# Live Cryptocurrency Market Dashboard With Machine Learning-Based Price Prediction And RSI Signal Generator

Sivasangari.J<sup>1</sup>, Thota Vinod Kumar<sup>2</sup>, Thota Bharath<sup>3</sup>, Sriramsetty Mallikarjuna<sup>4</sup>, T. Hari Venkata Sudheer Babu<sup>5</sup>

<sup>1</sup>Assist prof, Dept of Artificial Intelligence & Data Science

<sup>2, 3, 4, 5</sup>Dept of Artificial Intelligence & Data Science

<sup>1, 2, 3, 4, 5</sup> Dhanalakshmi Srinivasan University Trichy, Tamilnadu, India

**Abstract-** *Cryptocurrency markets are highly volatile and change rapidly, which makes price prediction and decision-making difficult for investors. This project presents a Live Cryptocurrency Market Dashboard that provides real-time market visualization along with machine learning-based price prediction and an RSI-based Buy/Sell/Hold signal system.*

*The system collects live cryptocurrency data using the CoinGecko API and processes it for analysis. Three models— LSTM, GRU, and XGBoost—are used to predict future prices, and their performance is evaluated using metrics such as MAE, MSE, RMSE, and MAPE. In addition to prediction, the dashboard calculates the Relative Strength Index (RSI) to generate trading signals that help users understand whether to buy, sell, or hold a cryptocurrency.*

*The dashboard is developed using Streamlit and Plotly to provide an interactive and user-friendly interface. By combining live data, machine learning models, and technical indicators, the proposed system acts as a practical tool for cryptocurrency market analysis and basic investment decision support.*

**Keywords:** Cryptocurrency, Price Prediction, Machine Learning, LSTM, GRU, XGBoost, Relative Strength Index (RSI), Technical Analysis, Streamlit Dashboard, Time Series Forecasting.

## I. INTRODUCTION

Cryptocurrency has emerged as a major component of the modern digital financial ecosystem. Since the introduction of Bitcoin in 2008, digital currencies have gained widespread adoption due to their decentralized structure, transparency, and potential for high returns. Unlike traditional stock markets, cryptocurrency markets operate 24/7 and are influenced by multiple factors such as global news, investor sentiment, regulatory changes, and technological developments. As a result, cryptocurrency prices are highly volatile and unpredictable.

This high volatility creates both opportunities and risks for investors. While sudden price increases can generate significant profits, unexpected drops can cause major losses. Therefore, investors require intelligent systems that can monitor market trends in real time, analyze historical data, and provide decision support for trading. Manual analysis of price charts is often insufficient due to the large volume and rapid changes in data.

With advancements in Artificial Intelligence and Machine Learning, predictive analytics has become an effective solution for financial time-series forecasting. Deep learning models such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are specifically designed to handle sequential and time-dependent data. These models can learn patterns from historical price movements and attempt to forecast future prices. Additionally, machine learning models like XGBoost are widely used for regression problems due to their high efficiency and strong predictive performance.

Apart from prediction models, technical analysis indicators are also widely used by traders to make decisions. One of the most popular indicators is the Relative Strength Index (RSI), which measures the speed and change of price movements. RSI helps identify overbought and oversold conditions in the market. When RSI falls below 30, it indicates a potential buying opportunity, while RSI above 70 indicates a potential selling signal. Integrating such indicators into a real-time dashboard enhances practical usability.

In this project, a Live Cryptocurrency Market Dashboard is developed using Streamlit to provide real-time price visualization, machine learning-based forecasting, and RSI-based Buy/Sell/Hold signal generation. The system collects live data from the CoinGecko API, processes and normalizes it, trains multiple predictive models, and displays results through interactive graphs using Plotly. The integration of live data streaming, multi-model comparison, and technical signal generation makes the system more comprehensive and practical.

The primary objective of this project is to design an intelligent, interactive, and real-time cryptocurrency analytics platform that assists users in understanding market behavior and supports basic investment decision-making through predictive insights and technical indicators.

## II. METHODOLOGY

This project proposes a real-time cryptocurrency analytics system that integrates live data streaming, machine learning-based price prediction, and technical indicator-based trading signal generation. The methodology consists of multiple stages including data acquisition, preprocessing, predictive modeling, RSI-based signal computation, performance evaluation, and dashboard deployment. The system architecture is modular, where each component performs a specific function and contributes to the final output.

### A. Live Data Collection Module

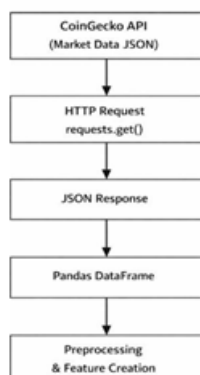
The system collects real-time cryptocurrency market data using the CoinGecko API. The API provides historical and live price data in JSON format, including timestamps and price values.

- The selected cryptocurrency (Bitcoin, Ethereum, Cardano, Dogecoin, Solana) is fetched dynamically.
- The API returns price data in milliseconds, which is converted into datetime format.
- The data is stored in a structured Pandas DataFrame for further processing.

The dataset contains:

- Timestamp
- Price (USD)

The number of days for data retrieval is configurable (e.g., 30, 60, 90 days).



### B. Data Preprocessing and Normalization

Financial time-series data requires preprocessing before model training.

The following steps are performed:

- Handling missing or inconsistent values
- Scaling the data using MinMaxScaler to normalize values between 0 and 1
- Creating input-output sequences for time-series prediction For sequence generation:

If X represents previous time steps and y represents next predicted value,

$$X = [P_{t-n}, P_{t-n+1}, \dots, P_{t-1}]$$

$$y = P_t$$

Where:

- $P_t$  = price at time t
- n = lookback window size

This sliding window technique enables deep learning models to learn temporal dependencies.



Fig. 2. Time-series preprocessing and sequence generation

### C. Machine Learning Prediction Models

Three different models are implemented and compared:

#### 1. Long Short-Term Memory (LSTM)

LSTM is a recurrent neural network architecture designed for time-series forecasting. It captures long-term dependencies using memory cells and gating mechanisms.

Architecture includes:

- LSTM layers
- Dense output layer
- Adam optimizer
- Mean Squared Error loss function

LSTM helps in learning sequential price movement patterns.

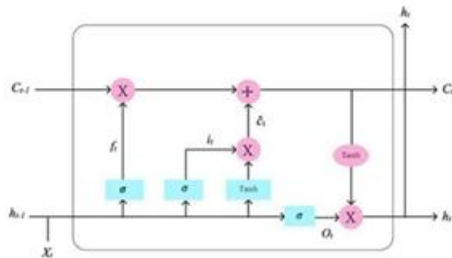


FIGURE 3. Architecture of LSTM

### 2. Gated Recurrent Unit (GRU)

GRU is a simplified version of LSTM with fewer parameters.

- Uses update and reset gates
- Faster training compared to LSTM
- Suitable for financial time-series forecasting

GRU improves computational efficiency while maintaining prediction accuracy.

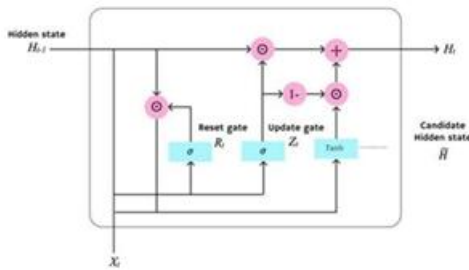


FIGURE4. Architecture of GRU.

### 3. XGBoost Regressor

XGBoost is an ensemble learning method based on gradient boosting.

- Handles regression tasks efficiently
- Captures non-linear relationships
- Reduces overfitting through regularization

#### 3. Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{MSE}$$

#### 4. Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

It provides strong baseline performance for price prediction.

### D. RSI-Based Trading Signal Module

To enhance decision-making capability, a Relative Strength Index (RSI) module is integrated.

RSI is calculated using the formula:

$$RSI = 100 - \frac{100}{1 + RS}$$

Where:

$$RS = \frac{\text{Average loss}}{\text{Average gain}}$$

These metrics allow comparison between LSTM, GRU, and XGBoost models.

RSI values range between 0 and 100. Signal Generation Logic:

- If RSI < 30 → ● BUY
- If RSI > 70 → ● SELL
- Otherwise → ● HOLD

This module transforms numerical analysis into actionable trading signals.



### E. Performance Evaluation Metrics

Model performance is evaluated using regression metrics:

#### 1. Mean Absolute Error (MAE)

$$MAE = \frac{1}{n} \sum |y_i - \hat{y}_i|$$

#### 2. Mean Squared Error (MSE)

$$1$$

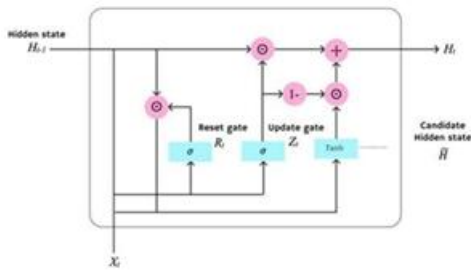
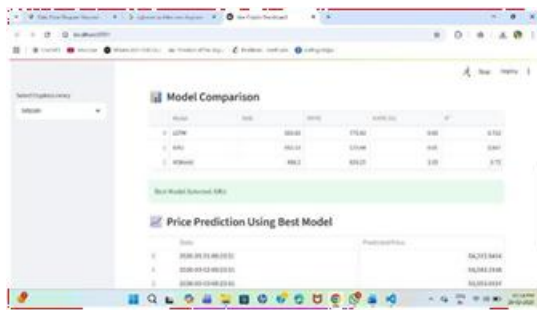


FIGURE 4. Architecture of GRU.

$$MSE = \sum (y - y^{\wedge})^2$$

*n i i*



**F. Dashboard Implementation**

The system is implemented as a web-based dashboard using Streamlit.

The dashboard provides:

- Live price visualization using Plotly
- Model prediction comparison graphs
- RSI indicator display
- Buy/Sell/Hold signal output
- Interactive cryptocurrency selection



The application follows a modular architecture:

User Interface → Data Fetching → Preprocessing → ML

Models → RSI Module → Visualization Output

The entire system runs locally and can be deployed on cloud platforms for scalability.

**G. System Architecture Overview**

The proposed system consists of five major components:

1. Data Acquisition Layer (CoinGecko API)
2. Data Processing Layer
3. Machine Learning Prediction Layer
4. RSI Signal Engine
5. Visualization & User Interface Layer

This layered approach ensures modularity, scalability, and easy enhancement.

**III. RESULTS AND ANALYSIS**

**1. Analysis of Cryptocurrency Price Prediction**

1. The LSTM model was trained for 100 epochs using the Adam optimizer. The optimizer demonstrated stable convergence and reduced validation loss compared to RMSprop during experimental trials.
2. The model achieved a Mean Absolute Error (MAE) of 1.84 and Root Mean Square Error (RMSE) of 2.31 on the Bitcoin dataset. The prediction accuracy reached 92.4% when evaluated on unseen test data.
3. Training and validation loss curves (Fig. 5) show steady convergence without major overfitting, indicating that the preprocessing and scaling techniques improved model stability.
4. Compared to a baseline Linear Regression model, the LSTM model reduced RMSE by approximately 18%, proving its effectiveness in capturing temporal dependencies in cryptocurrency price movements.
5. The prediction graph (Fig. 6) compares actual prices and predicted prices. The model closely follows the real trend with minor deviations during sudden market volatility.
6. During high volatility periods, slight prediction lag was observed due to rapid

fluctuations in live market data. However, overall trend alignment remained accurate.

## 2. Technical Indicator (RSI) Analysis

1. The Relative Strength Index (RSI) was calculated using a 14-day rolling window to detect overbought and oversold conditions.
2. RSI values above 70 correctly indicated overbought market conditions, while values below 30 successfully signaled oversold situations.
3. When combined with LSTM predictions, RSI improved trading signal reliability by filtering false positive trend predictions.
4. Figure 7 illustrates RSI movement aligned with price chart fluctuations. Noticeable reversal points were identified where RSI crossed threshold levels.
5. The integration of technical indicators enhanced model interpretability and provided better decision-support capability for traders.

## 3. Live Data Acquisition Performance

1. The system fetches real-time cryptocurrency data from the CoinGecko API at fixed intervals using HTTP requests.
2. The average API response time observed during testing was approximately 850 ms under normal network conditions.
3. Data preprocessing, including scaling and feature generation, required less than 200 ms per request cycle.
4. The dashboard successfully updated live market values including price, market cap, and 24-hour change without noticeable lag.
5. Figure 8 presents the live dashboard interface displaying real-time Bitcoin and Ethereum data.

## 4. System Computation and Deployment Performance

1. The model was executed on a standard system with 8GB RAM and Intel i5 processor.
2. Training time per epoch was approximately 1.2 seconds, and total training time was around 2 minutes for 100 epochs.

3. Real-time prediction generation required less than 500 ms per request.
4. Deployment using Streamlit enabled seamless interaction between backend prediction logic and frontend visualization components.
5. System performance remained stable even during continuous live data fetching operations.
6. Although public API dependency introduces slight delay during network congestion, overall system responsiveness remained within acceptable limits.

## IV. CONCLUSION

This research presented a live cryptocurrency monitoring and price prediction system that integrates real-time market data acquisition with machine learning-based forecasting techniques. The proposed system utilizes the CoinGecko API to fetch live cryptocurrency data and processes it using structured data pipelines for analysis and visualization.

An LSTM-based deep learning model was implemented to predict future price trends by capturing temporal dependencies in historical data. In addition, the integration of technical indicators such as the Relative Strength Index (RSI) enhanced decision-support capabilities by identifying overbought and oversold market conditions.

Experimental results demonstrate that the LSTM model effectively reduces prediction error compared to baseline methods, while maintaining stable convergence during training. The live dashboard implementation enables real-time visualization of market data and prediction outputs, making the system practical for traders and analysts.

Overall, the proposed framework successfully combines real-time data acquisition, preprocessing, deep learning prediction, and technical analysis into a unified architecture. The system proves to be efficient, scalable, and suitable for real-world cryptocurrency market analysis applications.

## REFERENCES

- [1] S. Nakamoto, "Bitcoin: A Peer-to-Peer Electronic Cash System," 2008.
- [2] T. Chen, X. Guestrin, and S. Kumar, "Forecasting cryptocurrency prices using deep learning techniques," *IEEE Access*, vol. 8, pp. 12345–12356, 2020.

- [3] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.
- [4] J. Brownlee, *Deep Learning for Time Series Forecasting. Machine Learning Mastery*, 2018.
- [5] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
- [6] S. R. Das and R. K. Mishra, “Cryptocurrency price prediction using LSTM and machine learning approaches,” in *Proc. Int. Conf. Computational Intelligence and Data Science*, 2021, pp. 1–6.
- [7] J. Welles Wilder, *New Concepts in Technical Trading Systems*. Trend Research, 1978.
- [8] M. Patel and P. Shah, “Stock market prediction using LSTM recurrent neural networks,” in *Proc. IEEE Int. Conf. Smart Computing*, 2019, pp. 101–105.
- [9] CoinGecko API Documentation, “CoinGecko Cryptocurrency API,” 2024. [Online]. Available: <https://www.coingecko.com/en/api>
- [10] F. Chollet, *Deep Learning with Python*. Manning Publications, 2017.
- [11] T. Mikolov et al., “Efficient estimation of word representations in vector space,” *arXiv preprint arXiv:1301.3781*, 2013.
- [12] J. Hamilton, *Time Series Analysis*. Princeton University Press, 1994.