

Pipeline Architecture

Step-by-Step Breakdown

1. Data Collection

-Input data is sourced from two CSV files:

- coin_gecko_2022-03-16.csv
- coin_gecko_2022-03-17.csv

-These contain daily market statistics such as:

- Cryptocurrency name
- Price
- 1h, 24h, and 7d price changes
- Market capitalization
- 24h trading volume (target variable)

2. Data Preprocessing

- The data from both files is merged using pandas.
- Null values are removed to ensure data consistency (dropna()).
- Date columns are formatted correctly.
- All numerical columns (price, volume, mkt_cap, etc.) are normalized using StandardScaler to improve model performance and ensure uniform scale.

3. Feature Engineering

Two new derived features are created to enhance model learning:

- **price_change_score:** A weighted score calculated from short-term price changes:

$$\text{price_change_score} = 0.2 \times 1h + 0.3 \times 24h + 0.5 \times 7d$$
$$\text{price_change_score} = 0.2 \times \text{price_change_1h} + 0.3 \times \text{price_change_24h} + 0.5 \times \text{price_change_7d}$$

- **volume_to_marketcap:** Measures liquidity by comparing 24h volume with market cap.

These features provide better insights into market movement and liquidity patterns.

4. Train/Test Split

- The preprocessed dataset is split using `train_test_split()` into:
 - 80% for training the model
 - 20% for testing and evaluating performance

5. Model Training

- The XGBoost regression model is selected (`XGBRegressor`) for its ability to handle complex, tabular data effectively.
- A `GridSearchCV` is used to tune model parameters (`max_depth`, `n_estimators`, `learning_rate`).
- Features used:
 - Scaled price
 - price_change_score
 - volume_to_marketcap
 - Scaled market cap
- Target: Scaled 24h_volume

6. Model Evaluation

After training, we check how well the model works:

- R^2 Score $\approx 0.92 \rightarrow$ model explains 92% of liquidity variation
- RMSE and MAE are low \rightarrow errors are small

This means the model is highly accurate.

7. Model Persistence

- The trained model is saved using pickle as `xgb_model.pkl`.
- The target scaler is also saved as `volume_scaler.pkl` to allow reverse transformation during prediction.

8. Deployment via Streamlit

- A simple web interface is created using Streamlit (`app.py`).
- Users provide four input values:
 - Price
 - Price Change Score
 - Volume-to-Market Cap Ratio
 - Market Cap
- The saved model (`xgb_model.pkl`) is loaded, and the model predicts the 24-hour trading volume.
- Results are shown immediately in the web interface.

Final Pipeline Flow

