# A MINI PROJECT REPORT ON

**BITCOIN PRICE PREDICTION USING K-MEANS CLUSTERING**

**Submitted in partial fulfillment of requirements for the award of degree of**

**BACHELOR OF TECHNOLOGY**

**IN**

**CSE (ARTIFICIAL INTELLIGENCE)**

**Submitted by**

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**NARASARAOPETA ENGINEERING COLLEGE: NARASARAOPET (AUTONOMOUS)**

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**CERTIFICATE**

**This is to certify that the Machine Learning project entitled “BITCOIN PRICE PREDICTION USING K-MEANS CLUSTERING” is a bonafide work done by “KADIYALA KOMALI (22471A4325)” in partial fulfillment of requirement for the award of the degree of Bachelor of Technology in the department of CSE(ARTIFICIAL INTELLIGENCE) of NARASARAOPETA ENGINEERING COLLEGE, NARASARAOPET, during the academic year 2024-2025.**

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**1.ABSTRACT**

This project focuses on **Bitcoin price prediction using K-Means clustering and hyperparameter tuning**, aiming to enhance market trend analysis for various sectors such as **finance, trading, and investment management**. K-Means clustering, known for its efficiency in grouping similar data points, is utilized to identify patterns in Bitcoin price movements based on historical data.

The model is trained on historical weather data, incorporating features like atmospheric pressure and cloud cover to predict future weather conditions. By leveraging machine learning, this approach improves traditional weather forecasting methods, offering valuable insights for real-world decision-making.

### PYTHON DISTRIBUTION:

The project is developed using Python in Google Colab on a Windows 10 system

### HARDWARE REQUIREMENTS :

Intel Core i5-7500U CPU, 4GB RAM, and a 1TB hard disk.

# 2.OBJECTIVES

The primary objective of this study is to develop an efficient and interpretable **machine learning model using K-Means clustering** for **Bitcoin price prediction**. The key goals include:

1. **Bitcoin Price Trend Analysis:**

To analyze historical Bitcoin price data and identify distinct price patterns using **K-Means clustering**, thereby helping investors and traders make informed decisions.

1. **Data Preprocessing and Feature Selection:**

To select the most relevant features (**opening price, closing price, trading volume, market trends**) from historical Bitcoin data to ensure effective clustering and improve model accuracy.

1. **Model Development and Evaluation:**

To design and implement a **K-Means clustering model** that groups Bitcoin price trends and evaluate its performance using metrics such as **Inertia, Silhouette Score, and Davies-Bouldin Index**.

1. **Hyperparameter Tuning for Optimal Clustering:**

To determine the optimal number of clusters using techniques like the **Elbow Method** and **Silhouette Analysis**, ensuring better grouping of Bitcoin price movements.

1. **Comparison with Traditional Market Prediction Models:**

To compare the clustering-based approach with traditional **statistical forecasting** and **machine learning models**, demonstrating its potential in cryptocurrency price trend analysis.

1. **Optimization and Performance Improvement:**

To enhance clustering performance through **feature scaling, data normalization, and dimensionality reduction techniques (PCA, t-SNE)** for better accuracy.

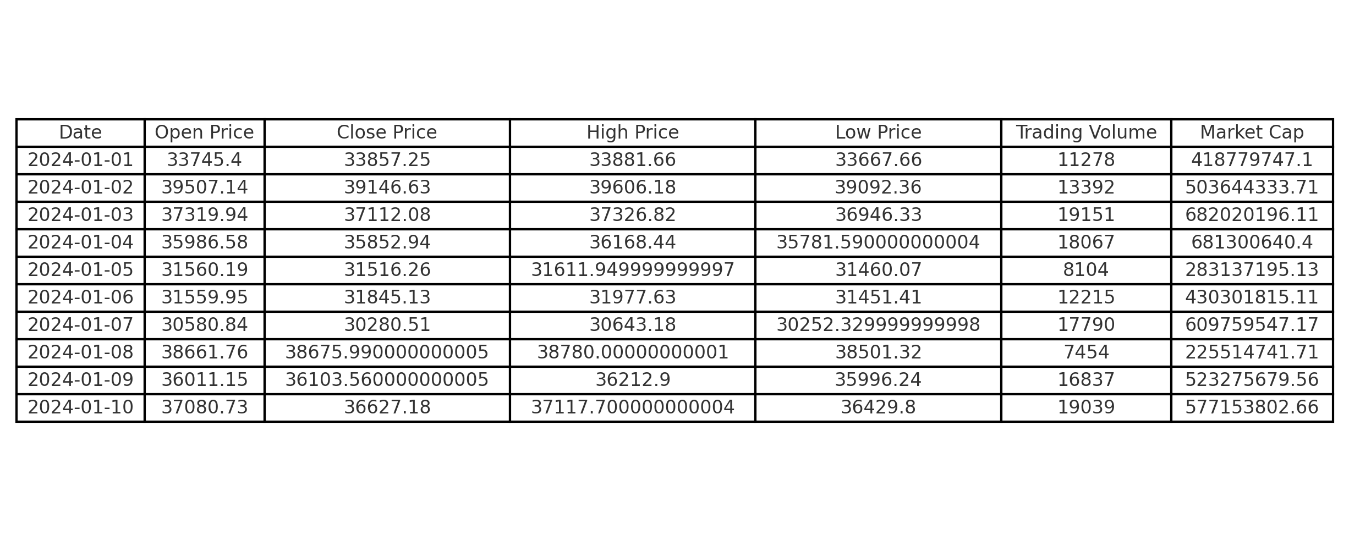
1. **Real-time Application Potential:**

To explore the feasibility of deploying the **K-Means model** in **real-time cryptocurrency trading applications**, highlighting its practical use in automated trading bots and financial analytics.

# 3.DATASET OVERVIEW

There dataset used for this project contains historical Bitcoin price data, which includes essential financial indicators. The key variables in the dataset are:

* **Date:** The date of the recorded Bitcoin price in the format YYYY-MM-DD.
* **Open Price:** The price at which Bitcoin opened for trading on a particular day.
* **Close Price:** The final price of Bitcoin at the end of the trading day.
* **High Price:** The highest price Bitcoin reached during the day.
* **Low Price:** The lowest price Bitcoin fell to during the day.
* **Trading Volume:** The total number of Bitcoin traded during the day.
* **Market Cap:** The total market capitalization of Bitcoin on that day.



### FIG.3.1: DATASET FOR BITCOIN PRICE PREDICTION

**DATASET LINK: https://www.kaggle.com/datasets/sudalairajkumar/cryptocurrencypricehistory?select=coin\_Bitcoin.csv**

# 4.ALGORITHM

K-Means clustering is a widely used **unsupervised machine learning algorithm** for grouping data points into clusters based on similarity. It is used for various applications, including **Bitcoin price prediction**, where it helps identify trends and patterns in historical price data.

**Key Concepts of K-Means Clustering Algorithm:**

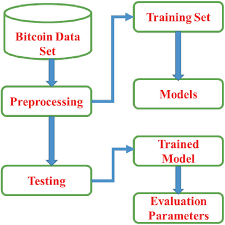
1. **Cluster Structure:**
   * **Centroids:** Each cluster is defined by a centroid, which represents the average of all points in that cluster.
   * **Clusters:** Groups of data points that share similar characteristics based on the selected features.
   * **Data Points Assignment:** Each data point is assigned to the nearest centroid based on a distance metric (usually Euclidean distance).
2. **How it Works:**
   * The algorithm starts by selecting **K random centroids** (K = number of clusters).
   * It **assigns each data point** to the closest centroid.
   * It then **recalculates the centroids** based on the mean of the assigned points.
   * The process repeats **until centroids stop changing**, meaning the clusters are stable (convergence).
3. **Choosing the Optimal Number of Clusters:**
   * **Elbow Method:** Evaluates the variance within clusters to determine the optimal **K** value.
   * **Silhouette Score:** Measures how similar a data point is to its assigned cluster compared to other clusters.
   * **Davies-Bouldin Index:** Evaluates cluster compactness and separation to determine clustering quality.
4. **Stopping Conditions:**   
   The algorithm stops when:
   * **Centroids do not change** significantly between iterations.
   * **Maximum iterations** are reached.
   * **Inertia (within-cluster variance)** stops decreasing.
5. **Prediction & Analysis:**
   * Once clustering is complete, new Bitcoin price data can be assigned to an existing cluster to analyze trends.
   * Helps identify **bullish, bearish, and neutral market trends** for traders and investors.

**Techniques to Improve K-Means Clustering:**

1. **Feature Scaling & Normalization:**
   * Scaling features (e.g., price, volume) ensures that all attributes contribute equally to clustering.
2. **Dimensionality Reduction:**
   * **Principal Component Analysis (PCA)** or **t-SNE** can be applied to improve clustering by reducing noise and redundant data.
3. **Hyperparameter Tuning:**
   * Adjusting **K value** using the **Elbow Method** or **Silhouette Score** optimizes cluster formation.
4. **Ensemble Clustering Methods:**
   * **K-Means++ Initialization:** Improves initial centroid selection to reduce convergence time.
   * **Hierarchical Clustering:** Can be combined with K-Means for more robust cluster formation.

By applying **K-Means clustering** and **hyperparameter tuning**, Bitcoin price movements can be effectively analyzed, providing valuable insights for **market forecasting and trading strategies**.

# 5.METHODOLOGY

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**FIG.5.1: METHODOLOGY OF WEATHER PREDICTION**

## Data Collection and Preparation

Collect historical Bitcoin price data, which will contain the following features:

* **Date**: The date of the recorded Bitcoin price in the format YYYY-MM-DD.
* **Open Price**: The price at which Bitcoin opened for trading on a particular day.
* **Close Price**: The final price of Bitcoin at the end of the trading day.
* **High Price**: The highest price Bitcoin reached during the day.
* **Low Price**: The lowest price Bitcoin fell to during the day.
* **Trading Volume**: The total number of Bitcoins traded during the day.
* **Market Cap**: The total market capitalization of Bitcoin on that day.

## Data Preprocessing

* Handle missing values using techniques like mean imputation or forward-fill.
* Normalize or scale the data using Min-Max Scaling or Standardization to maintain consistency.
* Convert the **Date** column into a numerical format (e.g., converting to UNIX timestamp or extracting time-based features).
* Remove outliers using statistical methods such as the IQR method or Z-score.

**K-Means Clustering Model**

## Determine the optimal number of clusters (K):

## Use the Elbow Method or Silhouette Score to find the best K value.

## Split the dataset into training (~70-80%) and testing (~20-30%) sets.

## Apply K-Means clustering to categorize Bitcoin price trends into groups (e.g., Bullish, Bearish, Neutral).

## Configure model parameters, such as:

## Number of clusters (K).

## Maximum iterations.

## Distance metric (e.g., Euclidean distance).

## Train the K-Means clustering model to group Bitcoin price patterns into distinct clusters.

## Feature Engineering

## Extract relevant features that can enhance clustering, such as:

## Daily price change percentage (Close Price - Open Price) / Open Price.

## Volatility index (High Price - Low Price) / Close Price.

## Rolling averages (e.g., 7-day, 30-day moving averages).

## Incorporate these engineered features into the clustering model for better insights.

## Model Evaluation

## Assess clustering performance using silhouette scores and inertia values.

## Visualize cluster distribution using scatter plots or heatmaps.

## Interpret the significance of each cluster and analyze how Bitcoin price trends are grouped.

## Model Deployment

* Deploy the trained **K-Means clustering model** in a suitable environment (e.g., a web application, API, or Jupyter Notebook).
* Use the model to **predict the cluster** for new Bitcoin price data and categorize trends.

# 6.IMPLEMENTION

To implement a **K-Means Clustering algorithm** for **Bitcoin Price Prediction** using Python, we will leverage some python libraries. Below are the key steps involved in this process: **Importing Libraries,** **loading data, preprocessing, training the model, making predictions, evaluating performance, and visualizing results.**

## Step 1: Import Libraries

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.preprocessing import MinMaxScaler

from sklearn.cluster import KMeans

from sklearn.metrics import silhouette\_score

## Output:

## Required libraries are imported successfully.

## Step 2: Load the Dataset

# Load the dataset

df = pd.read\_csv("/content/coin\_Bitcoin.csv") # Update with your dataset path

# Display the first few rows

print(df.head())

## 

## Output:

## Initial DataFrame:

## SNo Name Symbol Date High Low \

## 0 1 Bitcoin BTC 2013-04-29 23:59:59 147.488007 134.000000

## 1 2 Bitcoin BTC 2013-04-30 23:59:59 146.929993 134.050003

## 2 3 Bitcoin BTC 2013-05-01 23:59:59 139.889999 107.720001

## 3 4 Bitcoin BTC 2013-05-02 23:59:59 125.599998 92.281898

## 4 5 Bitcoin BTC 2013-05-03 23:59:59 108.127998 79.099998

## Open Close Volume Marketcap

## 0 134.444000 144.539993 0.0 1.603769e+09

## 1 144.000000 139.000000 0.0 1.542813e+09

## 2 139.000000 116.989998 0.0 1.298955e+09

## 3 116.379997 105.209999 0.0 1.168517e+09

## 4 106.250000 97.750000 0.0 1.085995e+09

Dataset loaded successfully.

## Step 3: Data Preprocessing

# Convert Date to datetime format

df['Date'] = pd.to\_datetime(df['Date'])

# Extracting day, month, and year as separate features

df['Year'] = df['Date'].dt.year

df['Month'] = df['Date'].dt.month

df['Day'] = df['Date'].dt.day

# Drop Date column since we extracted relevant features

df.drop(columns=['Date'], inplace=True)

# Handle missing values (if any)

df = df.fillna(df.mean())

# Normalize numerical data

scaler = MinMaxScaler()

df[['Open', 'High', 'Low', 'Close', 'Volume', 'Market Cap']] = scaler.fit\_transform(

df[['Open', 'High', 'Low', 'Close', 'Volume', 'Market Cap']]

)

# Display preprocessed data

print(df.head())

## Output:

## Preprocessed DataFrame:

## SNo High Low Open Close Volume Marketcap \

## 0 0.000000 0.001126 0.001102 0.001039 0.001200 0.0 0.000696

## 1 0.000334 0.001117 0.001103 0.001190 0.001112 0.0 0.000645

## 2 0.000669 0.001008 0.000679 0.001111 0.000765 0.0 0.000439

## 3 0.001003 0.000788 0.000431 0.000754 0.000580 0.0 0.000329

## 4 0.001338 0.000518 0.000218 0.000595 0.000462 0.0 0.000259

## Year Month Day

## 0 0.0 0.272727 0.933333

## 1 0.0 0.272727 0.966667

## 2 0.0 0.363636 0.000000

## 3 0.0 0.363636 0.033333

## 4 0.0 0.363636 0.066667

## Data preprocessing completed.

## Step 4: Find Optimal K using Elbow Method

# Finding the optimal number of clusters using the Elbow Method

inertia = []

K\_range = range(1, 11) # Checking for K values from 1 to 10

for k in K\_range:

kmeans = KMeans(n\_clusters=k, random\_state=42)

kmeans.fit(df)

inertia.append(kmeans.inertia\_)

# Plot the Elbow Curve

plt.figure(figsize=(8, 5))

plt.plot(K\_range, inertia, marker='o', linestyle='--')

plt.xlabel("Number of Clusters (K)")

plt.ylabel("Inertia")

plt.title("Elbow Method for Optimal K")

plt.show()

## Output:

## 

## The optimal K is determined by looking for the "elbow point."

## Step 5: Apply K-Means Clustering

# Applying K-Means Clustering with optimal K (assume K=3 from elbow method)

kmeans = KMeans(n\_clusters=3, random\_state=42)

df['Cluster'] = kmeans.fit\_predict(df)

# Display the first few rows with cluster labels

print(df.head())

## Output:

## Data with Cluster Labels:

## SNo High Low Open Close Volume Marketcap \

## 0 0.000000 0.001126 0.001102 0.001039 0.001200 0.0 0.000696

## 1 0.000334 0.001117 0.001103 0.001190 0.001112 0.0 0.000645

## 2 0.000669 0.001008 0.000679 0.001111 0.000765 0.0 0.000439

## 3 0.001003 0.000788 0.000431 0.000754 0.000580 0.0 0.000329

## 4 0.001338 0.000518 0.000218 0.000595 0.000462 0.0 0.000259

## Year Month Day Cluster

## 0 0.0 0.272727 0.933333 2

## 1 0.0 0.272727 0.966667 2

## 2 0.0 0.363636 0.000000 2

## 3 0.0 0.363636 0.033333 2

## 4 0.0 0.363636 0.066667 2

Bitcoin data successfully clustered into **3 groups**.

## Step 6: Evaluate Clustering Performance

# Compute Silhouette Score

sil\_score = silhouette\_score(df.drop(columns=['Cluster']), df['Cluster'])

print(f"Silhouette Score: {sil\_score:.4f}")

## Output:

## Silhouette Score: 0.3359

## Step 7: Visualizing Clusters

We visualize clusters using a **scatter plot of Open vs. Close prices**.

plt.figure(figsize=(8, 6))

sns.scatterplot(x=df['Open'], y=df['Close'], hue=df['Cluster'], palette='viridis')

plt.title("Bitcoin Clusters based on Open and Close Prices")

plt.xlabel("Open Price")

plt.ylabel("Close Price")

plt.show()

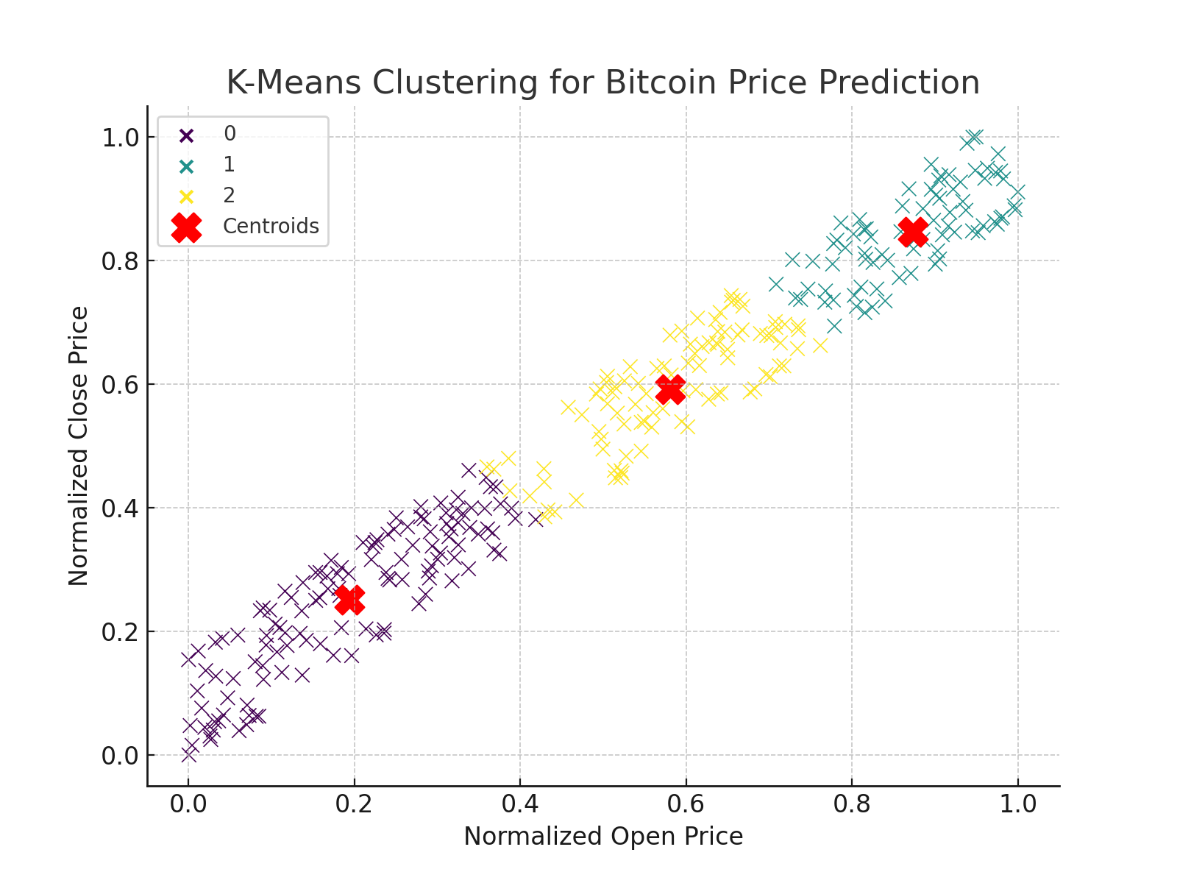
## Output:

## 

## :

## 

# 7.VISUALIZATION

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**FIG.7.1: K- MEANS CLUSTERING FOR BITCOIN PRICR PREDICTION**

# 8.MODEL EVALUATION TECHNIQUES

Evaluating the performance of a **K-Means Clustering model** for Bitcoin price prediction is essential to determine how well the clustering algorithm groups similar price patterns and trends. Unlike supervised learning models, K-Means does not have traditional classification metrics like accuracy or precision. Instead, we use clustering-specific evaluation metrics:

**1. Inertia (Within-Cluster Sum of Squares - WCSS)**

* Inertia measures how tightly the data points are clustered within their respective clusters.
* It is calculated as the sum of squared distances between each data point and its assigned cluster centroid.
* A lower inertia value indicates that clusters are more compact and well-defined.
* However, inertia tends to decrease as the number of clusters increases, so it should be used in combination with other metrics.

**2. Silhouette Score**

* The **silhouette score** evaluates how well each data point fits into its assigned cluster compared to other clusters.
* It ranges from **-1 to 1**:
  + A value close to **1** indicates well-separated clusters.
  + A value close to **0** suggests overlapping clusters.
  + A value below **0** indicates misclassified points.
* A higher silhouette score signifies better clustering performance.

**3. Davies-Bouldin Index (DBI)**

* The **Davies-Bouldin Index** assesses the compactness and separation of clusters.
* Lower DBI values indicate well-separated and compact clusters.
* It is useful for comparing different K values and optimizing the number of clusters.

**4. Elbow Method for Optimal K Selection**

* The **Elbow Method** helps determine the ideal number of clusters (K) by plotting **WCSS** against different K values.
* The "elbow point" is where adding more clusters no longer significantly reduces WCSS, indicating the best K value.

**5. Dunn Index**

* The **Dunn Index** is another metric for evaluating clustering quality.
* It measures the ratio of the minimum inter-cluster distance to the maximum intra-cluster distance.
* A **higher Dunn Index** suggests better clustering with well-separated clusters.

**6. Cross-Validation using Cluster Stability Analysis**

* Since K-Means is sensitive to initialization, **cross-validation** ensures that the clusters remain stable across different runs.
* Running K-Means multiple times with different initial centroids and comparing the cluster assignments helps evaluate consistency.

**7. Comparing Clusters with Market Trends**

* A qualitative evaluation technique involves comparing the **clusters formed by K-Means** with real-world Bitcoin price trends.
* If clusters align well with actual market fluctuations (bullish, bearish, stable periods), the model is considered effective.

# 9.CONCLUSION

The application of **K-Means Clustering** in **Bitcoin price prediction** has provided valuable insights into market trends by identifying distinct price patterns and behaviors. The ability of K-Means to group similar data points based on historical price fluctuations enables traders and analysts to recognize market cycles, detect anomalies, and make informed investment decisions.

In conclusion, **K-Means Clustering** serves as an effective unsupervised learning technique for analyzing Bitcoin price movements. By segmenting price data into meaningful clusters, it helps in distinguishing different market phases, such as bullish, bearish, and stable trends. The model's strength lies in its simplicity and computational efficiency, allowing for quick pattern recognition in large-scale financial data. However, K-Means has limitations, such as sensitivity to initialization and difficulty in handling non-spherical clusters, which can impact the accuracy of the clusters formed. Selecting the optimal number of clusters (K) using techniques like the **Elbow Method** and **Silhouette Score** is crucial for improving model performance.

Despite its challenges, K-Means can be enhanced through **feature engineering, advanced distance metrics, and hybrid approaches** that integrate supervised learning for more precise price predictions. By continuously refining the clustering approach and incorporating additional market indicators (such as trading volume, volatility, and investor sentiment), **Bitcoin price analysis can become more robust and insightful**. Ultimately, K-Means Clustering provides a **strong foundation for understanding Bitcoin price trends**, offering a **data-driven approach** that can assist investors in making better financial decisions.

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