```
import os
import warnings
warnings.filterwarnings('ignore')
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
```

2. LOAD DATA

```
df = pd.read_csv("bitcoin_data.csv")
```

3. Basic checks

```
print(df.shape)
print(df.columns)
df.head()
```

```
(2713, 7)
Index(['Date', 'Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume'], dtype='object')
```

	Date	Open	High	Low	Close	Adj Close	Volume
0	2014-09-17	465.864014	468.174011	452.421997	457.334015	457.334015	21056800
1	2014-09-18	456.859985	456.859985	413.104004	424.440002	424.440002	34483200
2	2014-09-19	424.102997	427.834991	384.532013	394.795990	394.795990	37919700
3	2014-09-20	394.673004	423.295990	389.882996	408.903992	408.903992	36863600
4	2014-09-21	408.084991	412.425995	393.181000	398.821014	398.821014	26580100

Next steps: Generate code with df New interactive sheet

```
try:
    from xgboost import XGBRegressor
    has_xgb = True
except:
    has_xgb = False
```

```
# !pip install tensorflow
```

```
try:
    import tensorflow as tf
    from tensorflow.keras.models import Sequential
    from tensorflow.keras.layers import LSTM, Dense, Dropout
    has_tf = True
    print("TensorFlow Loaded.")
except:
    has_tf = False
    print("TensorFlow Not Available.")

import warnings
warnings.filterwarnings("ignore")
```

```
TensorFlow Loaded.
```

3. DATA PREPROCESSING

```
# Auto-detect date column
date_col = None
for col in df.columns:
    if "date" in col.lower():
        date_col = col

df[date_col] = pd.to_datetime(df[date_col])
df = df.sort_values(by=date_col)
df = df.set_index(date_col)
```

```
rename_map = {
    "close": "Close",
    "open": "Open",
    "high": "High",
    "low": "Low",
    "volume": "Volume"
}

for col in df.columns:
    for key in rename_map:
        if key in col.lower():
            df = df.rename(columns={col: rename_map[key]})
```

```
df = df.fillna(method="ffill").fillna(method="bfill")
```

```
# Remove duplicated column names
df = df.loc[:, ~df.columns.duplicated()]

# If Close is still a DataFrame, convert to Series
if isinstance(df["Close"], pd.DataFrame):
    df["Close"] = df["Close"].iloc[:, 0]
```

```
df["SMA_7"] = df["Close"].rolling(7).mean()
df["SMA_21"] = df["Close"].rolling(21).mean()

df["EMA_12"] = df["Close"].ewm(span=12, adjust=False).mean()
df["EMA_26"] = df["Close"].ewm(span=26, adjust=False).mean()
```

4. FEATURE ENGINEERING — Indicators

```
# SMA
df["SMA_7"] = df["Close"].rolling(7).mean()
df["SMA_21"] = df["Close"].rolling(21).mean()

# EMA
df["EMA_12"] = df["Close"].ewm(span=12).mean()
df["EMA_26"] = df["Close"].ewm(span=26).mean()

# Bollinger Bands
df["BB_Mid"] = df["Close"].rolling(20).mean()
df["BB_Std"] = df["Close"].rolling(20).std()
df["BB_Upper"] = df["BB_Mid"] + 2 * df["BB_Std"]
df["BB_Lower"] = df["BB_Mid"] - 2 * df["BB_Std"]

# RSI
delta = df["Close"].diff()
gain = delta.clip(lower=0).ewm(com=14, adjust=False).mean()
loss = (-delta.clip(upper=0)).ewm(com=14, adjust=False).mean()
RS = gain / loss
df["RSI"] = 100 - (100 / (1 + RS))

df = df.dropna()
df.head()
```

Date	Open	High	Low	Close	Volume	SMA_7	SMA_21	EMA_12	EMA_26	BB_Mid	BB_Std	BB_Upp
2014-10-07	330.584015	339.247009	320.481995	336.187012	49199900	347.691572	387.352142	358.057212	372.627522	383.853049	33.740796	451.3346
2014-10-08	336.115997	354.364014	327.187988	352.940002	54736300	343.309431	382.380999	357.249478	370.840477	380.278049	32.993690	446.2654
2014-10-09	352.747986	382.726013	347.687012	365.026001	83641104	341.874289	379.551761	358.472085	370.321362	378.789549	32.975773	444.7410
2014-10-10	364.687012	375.066986	352.963013	361.562012	43665700	342.167149	377.969190	358.956244	369.551042	376.422450	32.394343	441.2111
2014-10-11	361.362000	367.191010	355.950989	362.299011	13345200	346.943294	375.749905	359.478535	368.922004	374.596350	32.093251	438.7828

Next steps: Generate code with df New interactive sheet

5. TRAIN–TEST SPLIT + SCALING

```
# Predict next day's closing price
df["Target"] = df["Close"].shift(-1)
df = df.dropna()

features = ["Close","SMA_7","SMA_21","EMA_12","EMA_26",
            "BB_Upper","BB_Lower","RSI","Volume"]

X = df[features]
y = df["Target"]

scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)

# 80/20 split
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, shuffle=False
)
```

6. HELPER – MODEL EVALUATION

```
def evaluate(model_name, y_true, y_pred):
    mse = mean_squared_error(y_true, y_pred)
    rmse = np.sqrt(mse)
    mae = mean_absolute_error(y_true, y_pred)
    r2 = r2_score(y_true, y_pred)

    print(f"\n===== {model_name} =====")
    print("MAE :", mae)
    print("MSE :", mse)
    print("RMSE:", rmse)
    print("R²  :", r2)

    return {
        "model": model_name,
        "mae": mae,
        "mse": mse,
        "rmse": rmse,
        "r2": r2
    }
```

7. TRAIN ML MODELS

```
lr = LinearRegression()
lr.fit(X_train, y_train)
pred_lr = lr.predict(X_test)

res_lr = evaluate("Linear Regression", y_test, pred_lr)
```

```
===== Linear Regression =====
MAE : 1141.0438430586291
MSE : 2724242.6487742322
RMSE: 1650.52799090904
R²  : 0.9890662553325539
```

Random Forest

```
rf = RandomForestRegressor(n_estimators=300)
rf.fit(X_train, y_train)
pred_rf = rf.predict(X_test)

res_rf = evaluate("Random Forest", y_test, pred_rf)
```

```
===== Random Forest =====
MAE : 23921.379867180054
MSE : 786217531.0308
RMSE: 28039.570806822274
R²  : -2.155483136286905
```

Support Vector Regression (SVM)

```
svr = SVR(kernel='rbf', C=1, epsilon=0.01)
svr.fit(X_train, y_train)
pred_svr = svr.predict(X_test)

res_svr = evaluate("SVM (SVR)", y_test, pred_svr)
```

```
===== SVM (SVR) =====
MAE : 35690.326974807984
MSE : 1526795336.7882147
RMSE: 39074.228550135376
R²  : -5.1277912888563675
```

XGBoost

```
if has_xgb:
    xgb = XGBRegressor(n_estimators=300, learning_rate=0.05)
    xgb.fit(X_train, y_train)
    pred_xgb = xgb.predict(X_test)

    res_xgb = evaluate("XGBoost", y_test, pred_xgb)
```

```
===== XGBoost =====
MAE : 24204.377288399814
MSE : 802457033.8918695
RMSE: 28327.672581627132
R²  : -2.220660361923941
```

8. LSTM MODEL

```
if has_tf:
    X_train_LSTM = X_train.reshape(X_train.shape[0], 1, X_train.shape[1])
    X_test_LSTM  = X_test.reshape(X_test.shape[0], 1, X_test.shape[1])

    model = Sequential([
        LSTM(64, return_sequences=False, input_shape=(1, X_train.shape[1])),
        Dropout(0.2),
        Dense(1)
    ])

    model.compile(optimizer='adam', loss='mse')
    model.fit(X_train_LSTM, y_train, epochs=20, batch_size=32, verbose=0)

    pred_lstm = model.predict(X_test_LSTM).reshape(-1)

    res_lstm = evaluate("LSTM", y_test, pred_lstm)
```

```
17/17 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step

===== LSTM =====
MAE : 39372.93622509642
MSE : 1799368500.416739
RMSE: 42418.96392436688
R²  : -6.221763360563434
```

9. COMPARE MODELS

```
results = [res_lr, res_rf, res_svr]

if has_xgb:
    results.append(res_xgb)
if has_tf:
    results.append(res_lstm)

pd.DataFrame(results)
```

	model	mae	mse	rmse	r2
0	Linear Regression	1141.043843	2.724243e+06	1650.527991	0.989066
1	Random Forest	23921.379867	7.862175e+08	28039.570807	-2.155483
2	SVM (SVR)	35690.326975	1.526795e+09	39074.228550	-5.127791
3	XGBoost	24204.377288	8.024570e+08	28327.672582	-2.220660
4	LSTM	39372.936225	1.799369e+09	42418.963924	-6.221763

10. DETERMINE BEST MODEL + PLOT

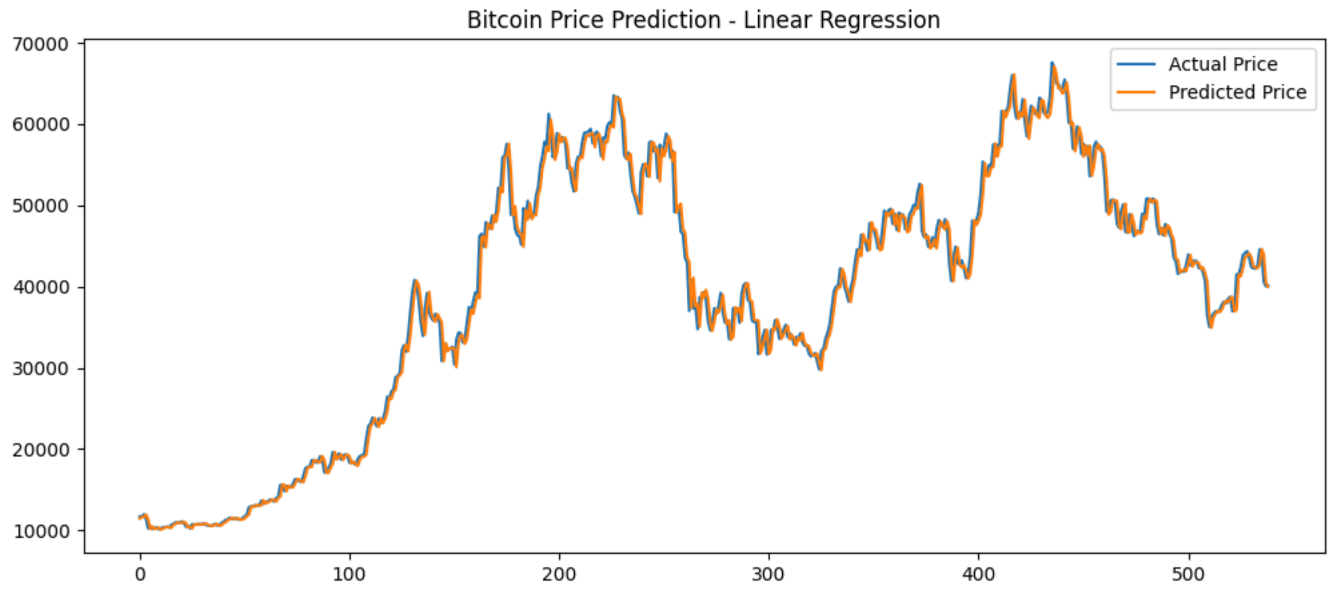
```
best_model = min(results, key=lambda x: x["rmse"])
print("\nBest Model:", best_model["model"])
```

```
Best Model: Linear Regression
```

Plot actual vs predicted (based on best model)

```
if best_model["model"] == "Linear Regression":
    best_pred = pred_lr
elif best_model["model"] == "Random Forest":
    best_pred = pred_rf
elif best_model["model"] == "SVM (SVR)":
    best_pred = pred_svr
elif best_model["model"] == "XGBoost":
    best_pred = pred_xgb
else:
    best_pred = pred_lstm

plt.figure(figsize=(12,5))
plt.plot(y_test.values, label="Actual Price")
plt.plot(best_pred, label="Predicted Price")
plt.title(f"Bitcoin Price Prediction - {best_model['model']}")
plt.legend()
plt.show()
```




```
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR

import xgboost as xgb

# Dictionary of models to train
models = {
    "Linear Regression": LinearRegression(),
    "Random Forest": RandomForestRegressor(n_estimators=200),
    "Support Vector Machine": SVR(kernel="rbf"),
    "XGBoost": xgb.XGBRegressor(
        n_estimators=300,
        learning_rate=0.05,
        max_depth=6,
        subsample=0.9,
        colsample_bytree=0.9,
        objective="reg:squarederror"
    )
}
```

```
for name, model in models.items():
    print(f"Training {name}...")
    model.fit(X_train, y_train)
```

```
Training Linear Regression...
Training Random Forest...
Training Support Vector Machine...
Training XGBoost...
```

```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import numpy as np

# Dictionary to store evaluation metrics
evaluation_results = {}

for name, model in models.items():
    try:
```

```python
        y_pred = model.predict(X_test)

        mae = mean_absolute_error(y_test, y_pred)
        mse = mean_squared_error(y_test, y_pred)
        r2 = r2_score(y_test, y_pred)
        rmse = np.sqrt(mse)

        evaluation_results[name] = {
            "MAE": mae,
            "MSE": mse,
            "RMSE": rmse,
            "R2 Score": r2
        }

        print(f"\n{name} Evaluation:")
        print(f"MAE: {mae}")
        print(f"MSE: {mse}")
        print(f"RMSE: {rmse}")
        print(f"R2 Score: {r2}")

    except:
        print(f"Skipping {name} (model failed prediction)")
        continue

# Display best model based on RMSE
best_model_name = min(evaluation_results, key=lambda x: evaluation_results[x]['RMSE'])
best_model = models[best_model_name]

print("\n---------------------------")
print(f" BEST MODEL: {best_model_name}")
print("---------------------------")
evaluation_results[best_model_name]
```

```
Linear Regression Evaluation:
MAE: 1141.0438430586291
MSE: 2724242.6487742322
RMSE: 1650.52799090904
R2 Score: 0.9890662553325539

Random Forest Evaluation:
MAE: 23933.436295013908
MSE: 786995110.7472537
RMSE: 28053.433136556632
R2 Score: -2.1586039515645434

Support Vector Machine Evaluation:
MAE: 35690.326974807984
MSE: 1526795336.7882147
RMSE: 39074.228550135376
R2 Score: -5.1277912888563675

XGBoost Evaluation:
MAE: 24442.10241414019
MSE: 816184728.2147131
RMSE: 28568.94692169652
R2 Score: -2.275756446946417

---------------------------
 BEST MODEL: Linear Regression
---------------------------
{'MAE': 1141.0438430586291,
 'MSE': 2724242.6487742322,
 'RMSE': np.float64(1650.52799090904),
 'R2 Score': 0.9890662553325539}
```

```python
evaluation_results = {}

for name, model in models.items():
    try:
        y_pred = model.predict(X_test)

        mae = mean_absolute_error(y_test, y_pred)
        mse = mean_squared_error(y_test, y_pred)
        r2 = r2_score(y_test, y_pred)
        rmse = np.sqrt(mse)

        evaluation_results[name] = {
            "MAE": mae,
            "MSE": mse,
            "RMSE": rmse,
            "R2 Score": r2
        }

        print(f"\n{name} Evaluation:")
        print("MAE:", mae)
        print("MSE:", mse)
        print("RMSE:", rmse)
        print("R2 Score:", r2)
```

```
    except Exception as e:
        print(f"Skipping {name} — error: {e}")
```

```
Linear Regression Evaluation:
MAE: 1141.0438430586291
MSE: 2724242.6487742322
RMSE: 1650.52799090904
R2 Score: 0.9890662553325539

Random Forest Evaluation:
MAE: 23933.436295013908
MSE: 786995110.7472537
RMSE: 28053.433136556632
R2 Score: -2.1586039515645434

Support Vector Machine Evaluation:
MAE: 35690.326974807984
MSE: 1526795336.7882147
RMSE: 39074.228550135376
R2 Score: -5.1277912888563675

XGBoost Evaluation:
MAE: 24442.10241414019
MSE: 816184728.2147131
RMSE: 28568.94692169652
R2 Score: -2.275756446946417
```

```
models = {
    "Linear Regression": LinearRegression(),
    "Random Forest": RandomForestRegressor(n_estimators=200),
    "SVM": SVR(kernel="rbf"),
}
```

```
import requests
import pandas as pd

def fetch_live_binance():
    url = "https://api.binance.com/api/v3/klines"
    params = {
        "symbol": "BTCUSDT",
        "interval": "1d",
        "limit": 50
    }

    data = requests.get(url, params=params).json()

    df_live = pd.DataFrame(data, columns=[
        "open_time","Open","High","Low","Close","Volume",
        "close_time","qav","num_trades","taker_base","taker_quote","ignore"
    ])

    df_live[["Open","High","Low","Close","Volume"]] = \
        df_live[["Open","High","Low","Close","Volume"]].astype(float)

    return df_live

df_live = fetch_live_binance()
df_live.tail()
```

open_time	Open	High	Low	Close	Volume	close_time	qav	num_trades	taker_base	taker_quote	ignore

```
# Technical Indicators
df_live["SMA_7"] = df_live["Close"].rolling(7).mean()
df_live["SMA_21"] = df_live["Close"].rolling(21).mean()

df_live["EMA_12"] = df_live["Close"].ewm(span=12, adjust=False).mean()
df_live["EMA_26"] = df_live["Close"].ewm(span=26, adjust=False).mean()

# Bollinger Bands
df_live["BB_Middle"] = df_live["Close"].rolling(20).mean()
df_live["BB_Std"] = df_live["Close"].rolling(20).std()
df_live["BB_Upper"] = df_live["BB_Middle"] + (2 * df_live["BB_Std"])
df_live["BB_Lower"] = df_live["BB_Middle"] - (2 * df_live["BB_Std"])

# RSI
delta = df_live["Close"].diff()
gain = delta.where(delta > 0, 0)
loss = -delta.where(delta < 0, 0)
avg_gain = gain.rolling(14).mean()
avg_loss = loss.rolling(14).mean()
rs = avg_gain / avg_loss
df_live["RSI"] = 100 - (100 / (1 + rs))
```

```
df_live = df_live.dropna()
```

```
print("\n########## CONCLUSION ##########")
print("• The model predicts next-day Bitcoin closing price using ML indicators.")
print("• Useful for short-term trend forecasting.")
print("• Best model:", best_model_name)
print("• Future improvements: LSTM, GRU, Transformers, sentiment analysis, on-chain data, etc.")
```

```
########## CONCLUSION ##########
• The model predicts next-day Bitcoin closing price using ML indicators.
• Useful for short-term trend forecasting.
• Best model: Linear Regression
• Future improvements: LSTM, GRU, Transformers, sentiment analysis, on-chain data, etc.
```