Financial Analysis of the Indian Banking Sector through Python and Machine Learning

Executive Summary

This project analyzes major Indian banking stocks using traditional financial metrics such as returns, volatility, Sharpe ratios and valuation multiples.

Python is used to automate data collection and analysis, while machine learning techniques are applied only to support insights related to behavioral regimes and market efficiency.

Key findings indicate that ICICI Bank delivered superior risk-adjusted returns, SBI appeared undervalued relative to profitability, and short-term return predictability remains limited, consistent with efficient market behavior.

Dataset Description

Dataset: Indian Banking Sector Stock Data
Source: Yahoo Finance (via yfinance Python library)
URL: https://finance.yahoo.com
Size: Daily observations across multiple years for selected major Indian banks
Domain: Financial Markets: Equity and Banking Sector Analysis
Region: India
Time Period: Multi-year historical data (covering different market conditions)

Key Components

Price Data:

- Daily Adjusted Closing Prices
- Used to compute returns, volatility, and trend indicators
- Adjusted prices account for dividends and stock splits to reflect true investor returns

Return and Risk Metrics:

- Daily and annualized returns
- Volatility (risk) measures
- Risk-adjusted performance metrics (e.g., Sharpe Ratio)

**Valuation and Profitability Metrics: **

- Price-to-Book (P/B) Ratio
- Price-to-Earnings (P/E) Ratio
- Return on Equity (ROE)

Derived Financial Indicators:

- Short-term and medium-term return measures
- Volatility-based indicators
- Moving averages to capture trend behavior

Machine Learning Inputs:

- Financial indicators derived from historical price data
- Used for behavioral pattern analysis and return predictability assessment

Introduction : Data Setup and Environment

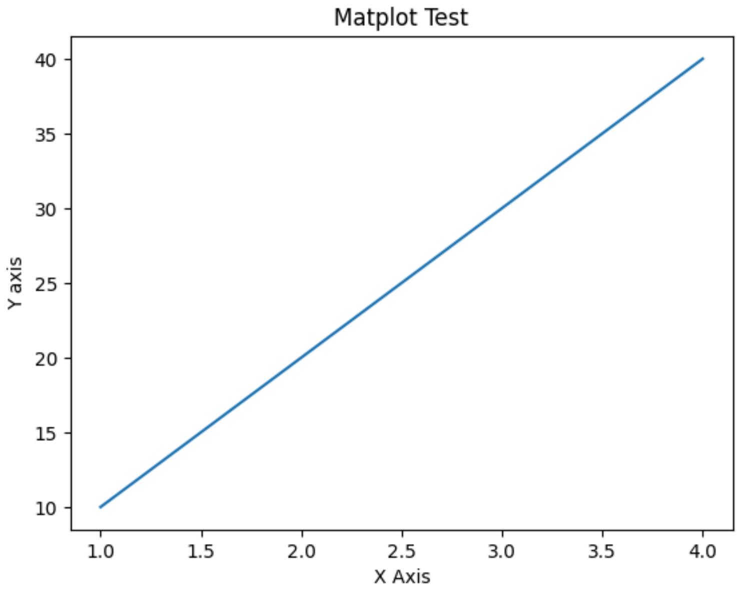
This section sets up the Python environment and imports the libraries required for financial analysis, data handling and visualization.

```
import pandas as pd
import numpy as np
import yfinance as yf
import matplotlib.pyplot as plt

from sklearn.preprocessing import StandardScaler
```

```python
from sklearn.cluster import KMeans
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier

print("All libraries imported successfully!")
```

```
All libraries imported successfully!
```

```python
x = [1, 2, 3, 4]
y = [10,20,30,40]

plt.plot(x,y)
plt.title("Matplot Test")
plt.xlabel("X Axis")
plt.ylabel("Y axis")
plt.show()
```




```python
sample_data = np.array([[1,2], [3,4], [5,6]])

scaler = StandardScaler()
scaled_data = scaler.fit_transform(sample_data)

print(scaled_data)
```

```
[[-1.22474487 -1.22474487]
 [ 0.          0.        ]
 [ 1.22474487  1.22474487]]
```

```
Start coding or generate with AI.
```

Section 1: Data Collection and Basic visualization

This section collects historical price data for major Indian banking stocks using adjusted closing prices.
Adjusted closing prices reflect true investor returns by accounting for dividends and stock splits, making them suitable for return and risk calculations in financial analysis.

```python
Banks = [
  'HDFCBANK.NS',
  'ICICIBANK.NS',
  'AXISBANK.NS',
  'KOTAKBANK.NS',
  'SBIN.NS'
]
```

```python
import yfinance as yf

price_data = yf.download(
    Banks,
    start='2020-04-01',
    end='2025-03-31',
```

```
    auto_adjust=False
)

price_data.head()
```

[*********************100%***********************] 5 of 5 completed

Price	Adj Close					Close			
Ticker	AXISBANK.NS	HDFCBANK.NS	ICICIBANK.NS	KOTAKBANK.NS	SBIN.NS	AXISBANK.NS	HDFCBANK.NS	ICICIBANK.NS	KOTAKBANK.N
Date									
2020-04-01	357.158722	392.912140	300.940430	1176.734009	172.132797	358.649994	414.825012	311.149994	1181.65002
2020-04-03	324.096771	385.429443	277.244263	1136.103516	161.936768	325.450012	406.924988	286.649994	1140.84997
2020-04-07	387.233154	424.382019	315.399872	1193.065796	171.994385	388.850006	448.049988	326.100006	1198.05004
2020-04-08	389.722778	420.972260	308.484467	1182.708984	168.857132	391.350006	444.450012	318.950012	1187.65002
2020-04-09	418.403015	438.092407	331.455200	1267.604248	173.240036	420.149994	462.524994	342.700012	1272.90002

5 rows × 30 columns

```
adj_close = price_data['Adj Close']
adj_close.head()
```

Ticker	AXISBANK.NS	HDFCBANK.NS	ICICIBANK.NS	KOTAKBANK.NS	SBIN.NS
Date					
2020-04-01	357.158722	392.912140	300.940430	1176.734009	172.132797
2020-04-03	324.096771	385.429443	277.244263	1136.103516	161.936768
2020-04-07	387.233154	424.382019	315.399872	1193.065796	171.994385
2020-04-08	389.722778	420.972260	308.484467	1182.708984	168.857132
2020-04-09	418.403015	438.092407	331.455200	1267.604248	173.240036

```
adj_close.shape
```

(1237, 5)

```
adj_close.isna().sum()
adj_close = adj_close.dropna()
adj_close.head()
```

Ticker	AXISBANK.NS	HDFCBANK.NS	ICICIBANK.NS	KOTAKBANK.NS	SBIN.NS
Date					
2020-04-01	357.158722	392.912140	300.940430	1176.734009	172.132797
2020-04-03	324.096771	385.429443	277.244263	1136.103516	161.936768
2020-04-07	387.233154	424.382019	315.399872	1193.065796	171.994385
2020-04-08	389.722778	420.972260	308.484467	1182.708984	168.857132
2020-04-09	418.403015	438.092407	331.455200	1267.604248	173.240036

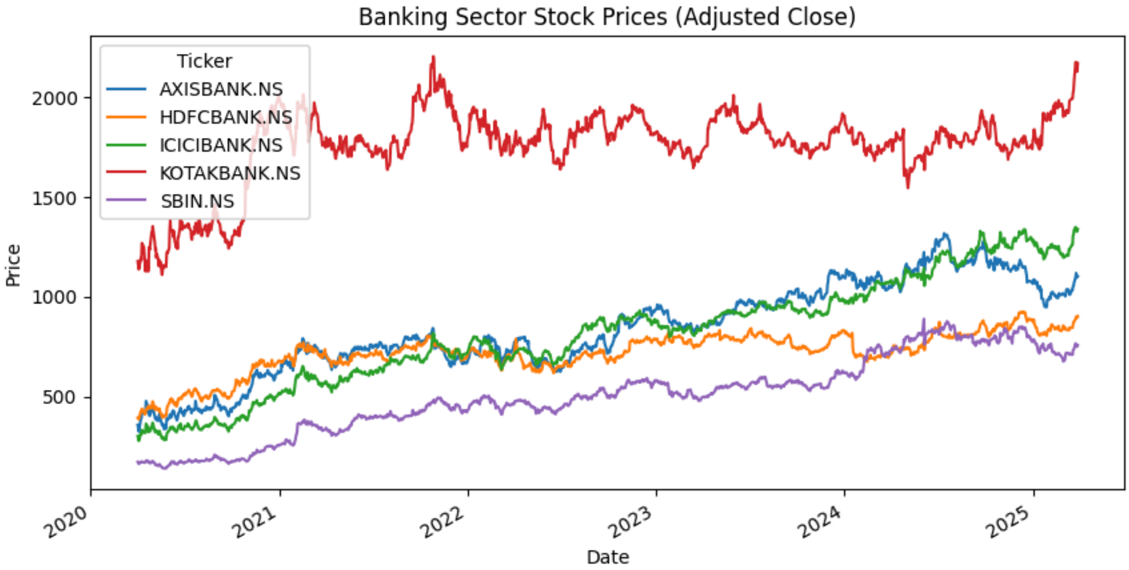
```
adj_close.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1237 entries, 2020-04-01 to 2025-03-28
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   AXISBANK.NS   1237 non-null   float64
 1   HDFCBANK.NS   1237 non-null   float64
 2   ICICIBANK.NS  1237 non-null   float64
 3   KOTAKBANK.NS  1237 non-null   float64
 4   SBIN.NS       1237 non-null   float64
dtypes: float64(5)
memory usage: 58.0 KB
```

```
adj_close.plot(figsize=(10,5))
plt.title("Banking Sector Stock Prices (Adjusted Close)")
```

```
plt.xlabel("Date")
plt.ylabel("Price")
plt.show
```

```
matplotlib.pyplot.show
def show(*args, **kwargs) -> None

Display all open figures.

Parameters
----------
block : bool, optional
    Whether to wait for all figures to be closed before returning.
```



Section 2: Risk & Returns Analysis

This section calculates daily and annual returns, volatility and Sharpe ratios to evaluate the performance of banking stocks on a risk-adjusted basis.
Returns alone do not capture investment quality hence Risk-adjusted metrics such as volatility and Sharpe ratio provide a more realistic comparison of performance across banks.

```
daily_returns = adj_close.pct_change()
daily_returns.head()
```

Ticker Date	AXISBANK.NS	HDFCBANK.NS	ICICIBANK.NS	KOTAKBANK.NS	SBIN.NS
2020-04-01	NaN	NaN	NaN	NaN	NaN
2020-04-03	-0.092569	-0.019044	-0.078740	-0.034528	-0.059234
2020-04-07	0.194807	0.101063	0.137625	0.050138	0.062108
2020-04-08	0.006429	-0.008035	-0.021926	-0.008681	-0.018240
2020-04-09	0.073591	0.040668	0.074463	0.071780	0.025956

```
daily_returns = daily_returns.dropna()
daily_returns.head()
```

Ticker Date	AXISBANK.NS	HDFCBANK.NS	ICICIBANK.NS	KOTAKBANK.NS	SBIN.NS
2020-04-03	-0.092569	-0.019044	-0.078740	-0.034528	-0.059234
2020-04-07	0.194807	0.101063	0.137625	0.050138	0.062108
2020-04-08	0.006429	-0.008035	-0.021926	-0.008681	-0.018240
2020-04-09	0.073591	0.040668	0.074463	0.071780	0.025956
2020-04-13	-0.002856	-0.032106	-0.035162	-0.017283	-0.022636

```
annual_returns = daily_returns.mean() * 252
annual_returns
```

	0
Ticker	
AXISBANK.NS	0.282052
HDFCBANK.NS	0.199820
ICICIBANK.NS	0.345391
KOTAKBANK.NS	0.160505
SBIN.NS	0.346773

dtype: float64

```
volatility = daily_returns.std() * np.sqrt(252)
volatility
```

	0
Ticker	
AXISBANK.NS	0.325929
HDFCBANK.NS	0.246778
ICICIBANK.NS	0.287329
KOTAKBANK.NS	0.268327
SBIN.NS	0.299425

dtype: float64

```
risk_return_table = pd.DataFrame({
    'Annual Return': annual_returns,
    'Volatility (Risk)': volatility
})

risk_return_table
```

	Annual Return	Volatility (Risk)
Ticker		
AXISBANK.NS	0.282052	0.325929
HDFCBANK.NS	0.199820	0.246778
ICICIBANK.NS	0.345391	0.287329
KOTAKBANK.NS	0.160505	0.268327
SBIN.NS	0.346773	0.299425

```
plt.figure(figsize=(8,6))
plt.scatter(
    risk_return_table['Volatility (Risk)'],
    risk_return_table['Annual Return']
)

for bank in risk_return_table.index:
    plt.text(
        risk_return_table.loc[bank, 'Volatility (Risk)'],
        risk_return_table.loc[bank, 'Annual Return'],
        bank
    )

plt.xlabel("Risk (Volatility)")
plt.ylabel("Return")
plt.title("Risk vs Return: Banking Stocks")
plt.show()
```

Show hidden output

```
risk_free_rate = 0.06

sharpe_ratio = (annual_returns - risk_free_rate) / volatility
sharpe_ratio
```

```
risk_return_table['Sharpe Ratio'] = sharpe_ratio
risk_return_table
```

Ticker	Annual Return	Volatility (Risk)	Sharpe Ratio
AXISBANK.NS	0.282052	0.325929	0.681291
HDFCBANK.NS	0.199820	0.246778	0.566584
ICICIBANK.NS	0.345391	0.287329	0.993254
KOTAKBANK.NS	0.160505	0.268327	0.374561
SBIN.NS	0.346773	0.299425	0.957745

```
risk_return_table.sort_values(by='Sharpe Ratio', ascending=False)
```

Ticker	Annual Return	Volatility (Risk)	Sharpe Ratio
ICICIBANK.NS	0.345391	0.287329	0.993254
SBIN.NS	0.346773	0.299425	0.957745
AXISBANK.NS	0.282052	0.325929	0.681291
HDFCBANK.NS	0.199820	0.246778	0.566584
KOTAKBANK.NS	0.160505	0.268327	0.374561

Double-click (or enter) to edit

Section 3: Valuation Metrics and Profitability Comparison

This section compares banks using valuation and profitability metrics such as Price-to-Book ratio, Price-to-Earnings ratio and Return on Equity Ratio.
Although Banks are primarily valued based on their book value and profitability. Comparing valuation multiples with ROE helps explain why certain banks trade at a premium or discount.

```
bank_tickers = {
    'HDFCBANK.NS': 'HDFC Bank',
    'ICICIBANK.NS': 'ICICI Bank',
    'AXISBANK.NS': 'Axis Bank',
    'KOTAKBANK.NS': 'Kotak Bank',
    'SBIN.NS': 'SBI'
}
```

```
valuation_data = []

for ticker, name in bank_tickers.items():
    info = yf.Ticker(ticker).info

    valuation_data.append({
        'Bank': name,
        'P/B Ratio': info.get('priceToBook'),
        'P/E Ratio': info.get('trailingPE'),
        'ROE': info.get('returnOnEquity')
    })

valuation_df = pd.DataFrame(valuation_data)
valuation_df
```

	Bank	P/B Ratio	P/E Ratio	ROE
0	HDFC Bank	2.783277	22.520567	0.10843
1	ICICI Bank	2.883211	18.315973	0.17599
2	Axis Bank	1.913056	14.750090	0.14004
3	Kotak Bank	2.555576	23.093786	0.11780
4	SBI	1.589422	10.905551	0.15676

```
valuation_df.set_index('Bank', inplace=True)
valuation_df
```

Bank	P/B Ratio	P/E Ratio	ROE
HDFC Bank	2.783277	22.520567	0.10843
ICICI Bank	2.883211	18.315973	0.17599
Axis Bank	1.913056	14.750090	0.14004
Kotak Bank	2.555576	23.093786	0.11780
SBI	1.589422	10.905551	0.15676

Section 4: Data Preparation for Machine Learning

In this section the financial data was transformed into a structured format that models can work with.
Price data was converted into indicators such as recent returns, volatility, and trend measures. These indicators capture short-term behavior and are commonly used to analyze price dynamics.

```
returns = adj_close.pct_change().dropna()
returns.head()
```

Ticker / Date	AXISBANK.NS	HDFCBANK.NS	ICICIBANK.NS	KOTAKBANK.NS	SBIN.NS
2020-04-03	-0.092569	-0.019044	-0.078740	-0.034528	-0.059234
2020-04-07	0.194807	0.101063	0.137625	0.050138	0.062108
2020-04-08	0.006429	-0.008035	-0.021926	-0.008681	-0.018240
2020-04-09	0.073591	0.040668	0.074463	0.071780	0.025956
2020-04-13	-0.002856	-0.032106	-0.035162	-0.017283	-0.022636

```
returns_long = returns.stack().reset_index()
returns_long.columns = ['Date', 'Ticker', 'Daily_Return']
returns_long.head()

features = returns_long.copy()
features.head()
```

	Date	Ticker	Daily_Return
0	2020-04-03	AXISBANK.NS	-0.092569
1	2020-04-03	HDFCBANK.NS	-0.019044
2	2020-04-03	ICICIBANK.NS	-0.078740
3	2020-04-03	KOTAKBANK.NS	-0.034528
4	2020-04-03	SBIN.NS	-0.059234

```
features['Return_1M'] = (
    features.groupby('Ticker')['Daily_Return']
    .rolling(21)
    .mean()
    .reset_index(level=0, drop=True)
)

features['Return_3M'] = (
    features.groupby('Ticker')['Daily_Return']
    .rolling(63)
    .mean()
    .reset_index(level=0, drop=True)
)

features['Volatility_1M'] = (
    features.groupby('Ticker')['Daily_Return']
    .rolling(21)
    .std()
    .reset_index(level=0, drop=True)
)
```

```
prices_long = adj_close.stack().reset_index()
prices_long.columns = ['Date', 'Ticker', 'Adj_Close']

features = features.merge(prices_long, on=['Date', 'Ticker'])
features.head()
```

	Date	Ticker	Daily_Return	Return_1M	Return_3M	Volatility_1M	Adj_Close
0	2020-04-03	AXISBANK.NS	-0.092569	NaN	NaN	NaN	324.096771
1	2020-04-03	HDFCBANK.NS	-0.019044	NaN	NaN	NaN	385.429443
2	2020-04-03	ICICIBANK.NS	-0.078740	NaN	NaN	NaN	277.244263
3	2020-04-03	KOTAKBANK.NS	-0.034528	NaN	NaN	NaN	1136.103516
4	2020-04-03	SBIN.NS	-0.059234	NaN	NaN	NaN	161.936768

```
features['MA_20'] = (
    features.groupby('Ticker')['Adj_Close']
    .rolling(20)
    .mean()
    .reset_index(level=0, drop=True)
)

features['MA_50'] = (
    features.groupby('Ticker')['Adj_Close']
    .rolling(50)
    .mean()
    .reset_index(level=0, drop=True)
)

future_return = (
    features.groupby('Ticker')['Daily_Return']
    .shift(-21)
)

features['Target'] = (future_return > 0).astype(int)
```

```
features_clean = features.dropna()
features_clean.head()
```

	Date	Ticker	Daily_Return	Return_1M	Return_3M	Volatility_1M	Adj_Close	MA_20	MA_50	Target
310	2020-07-07	AXISBANK.NS	0.030760	0.002324	0.004787	0.031325	445.489929	416.003035	402.184728	1
311	2020-07-07	HDFCBANK.NS	0.001949	0.004228	0.005003	0.021084	523.385559	490.228517	460.605833	0
312	2020-07-07	ICICIBANK.NS	0.039243	0.002516	0.003950	0.029142	363.710876	342.505293	330.454138	1

```
X = features_clean.drop(columns=['Date', 'Ticker', 'Target'])
y = features_clean['Target']

split_index = int(len(features_clean) * 0.7)

X_train = X.iloc[:split_index]
X_test = X.iloc[split_index:]

y_train = y.iloc[:split_index]
y_test = y.iloc[split_index:]

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Section 5: Identifying Behavioral Patterns Using Unsupervised Learning

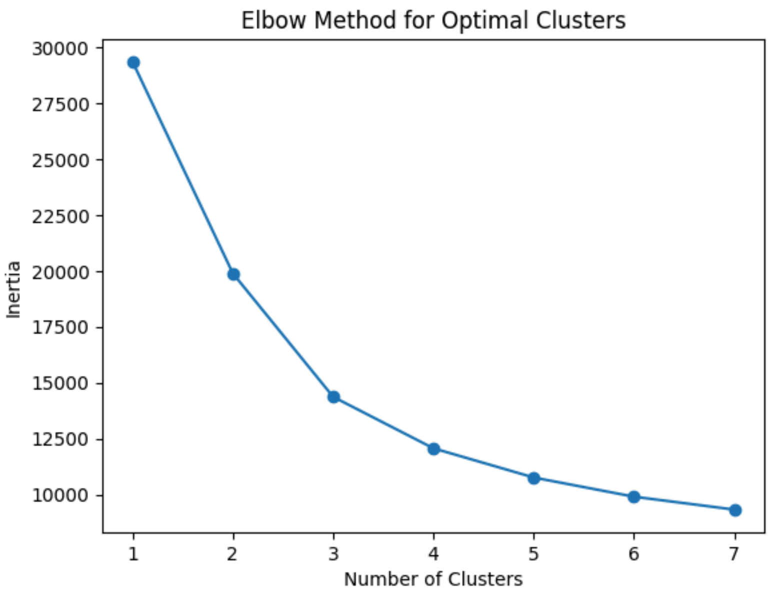
This section analyzes patterns in banking stock behavior using unsupervised machine learning techniques.
By grouping observations based on return, volatility and trend characteristics, the analysis highlights different behavioral patterns that

emerge over time, Rather than classifying individual banks, this approach helps understand how banking stocks move through periods of stability, transition, and higher risk under varying market conditions.

```
cluster_features = features_clean[
    ['Return_1M', 'Return_3M', 'Volatility_1M', 'MA_20', 'MA_50']
]

cluster_features.head()
```

	Return_1M	Return_3M	Volatility_1M	MA_20	MA_50
310	0.002324	0.004787	0.031325	416.003035	402.184728
311	0.004228	0.005003	0.021084	490.228517	460.605833
312	0.002516	0.003950	0.029142	342.505293	330.454138
313	0.001377	0.002836	0.023743	1325.056775	1271.090703
314	0.000746	0.000611	0.024538	168.469594	161.254875

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
cluster_scaled = scaler.fit_transform(cluster_features)

from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

inertia = []

for k in range(1, 8):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(cluster_scaled)
    inertia.append(kmeans.inertia_)

plt.plot(range(1, 8), inertia, marker='o')
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.title('Elbow Method for Optimal Clusters')
plt.show()
```

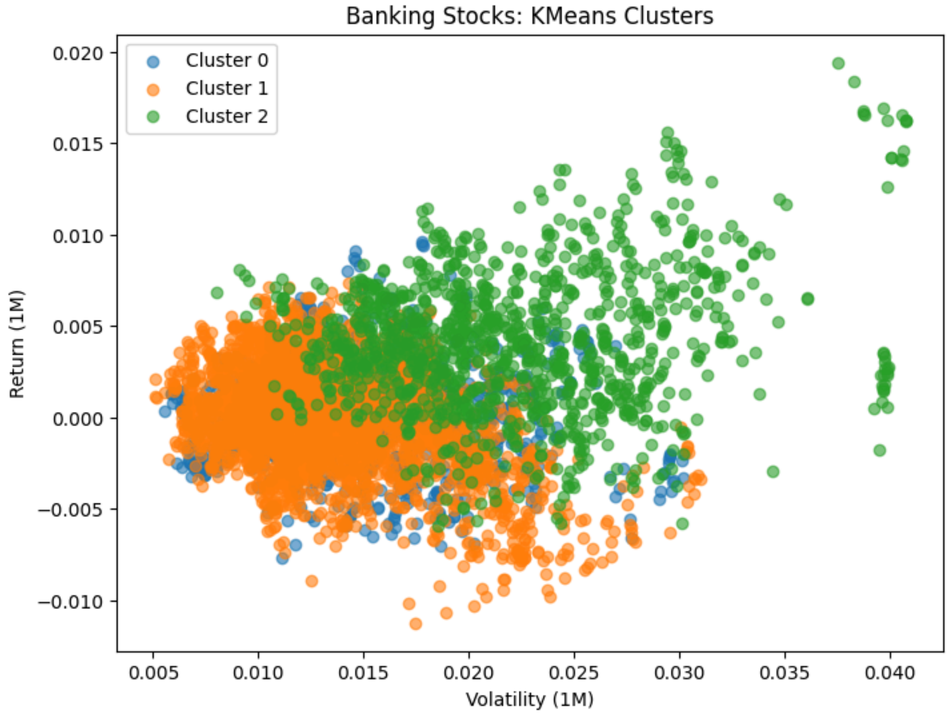



```
kmeans = KMeans(n_clusters=3, random_state=42)
clusters = kmeans.fit_predict(cluster_scaled)

features_clean['Cluster'] = clusters
features_clean[['Ticker', 'Cluster']].head()

features_clean.groupby(['Ticker', 'Cluster']).size()

cluster_summary = features_clean.groupby('Cluster')[
    ['Return_1M', 'Return_3M', 'Volatility_1M']
].mean()

cluster_summary
```

```
/tmp/ipython-input-2889351149.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view
  features_clean['Cluster'] = clusters
```

Cluster	Return_1M	Return_3M	Volatility_1M
0	0.000251	0.000424	0.014566
1	0.000022	0.000417	0.013238
2	0.004147	0.003038	0.022051

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

for cluster in sorted(features_clean['Cluster'].unique()):
    subset = features_clean[features_clean['Cluster'] == cluster]
    plt.scatter(
        subset['Volatility_1M'],
        subset['Return_1M'],
        label=f'Cluster {cluster}',
        alpha=0.6
    )

plt.xlabel('Volatility (1M)')
plt.ylabel('Return (1M)')
plt.title('Banking Stocks: KMeans Clusters')
plt.legend()
plt.show()
```



Section 6: Evaluation of Short Term Return Predictability

This section evaluates whether short-term movements in banking stock returns can be explained using historical financial indicators. Machine learning models were applied to assess whether patterns in past returns, volatility and trends translate into reliable signals about future price direction.
The focus of this analysis is not on building a trading strategy but on understanding the extent to which banking stock returns are predictable in the short term.

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

log_model = LogisticRegression(max_iter=1000)
log_model.fit(X_train_scaled, y_train)
```

```
y_pred_log = log_model.predict(X_test_scaled)

print("Logistic Regression Accuracy:", accuracy_score(y_test, y_pred_log))
print(confusion_matrix(y_test, y_pred_log))
print(classification_report(y_test, y_pred_log))
```

```
Logistic Regression Accuracy: 0.5059625212947189
[[139 751]
 [119 752]]
              precision    recall  f1-score   support

           0       0.54      0.16      0.24       890
           1       0.50      0.86      0.63       871

    accuracy                           0.51      1761
   macro avg       0.52      0.51      0.44      1761
weighted avg       0.52      0.51      0.44      1761
```

```
from sklearn.ensemble import RandomForestClassifier

rf_model = RandomForestClassifier(
    n_estimators=200,
    max_depth=6,
    random_state=42
)

rf_model.fit(X_train, y_train)

y_pred_rf = rf_model.predict(X_test)

print("Random Forest Accuracy:", accuracy_score(y_test, y_pred_rf))
print(confusion_matrix(y_test, y_pred_rf))
print(classification_report(y_test, y_pred_rf))
```

```
Random Forest Accuracy: 0.49744463373083475
[[153 737]
 [148 723]]
              precision    recall  f1-score   support

           0       0.51      0.17      0.26       890
           1       0.50      0.83      0.62       871

    accuracy                           0.50      1761
   macro avg       0.50      0.50      0.44      1761
weighted avg       0.50      0.50      0.44      1761
```

```
feature_importance = pd.Series(
    rf_model.feature_importances_,
    index=X.columns
).sort_values(ascending=False)

feature_importance
```

	0
Daily_Return	0.200372
Return_1M	0.158933
Adj_Close	0.143410
Return_3M	0.133918
MA_20	0.130214
Volatility_1M	0.118750
MA_50	0.114403

dtype: float64

Section 7: Model Evaluation and Consolidated Results

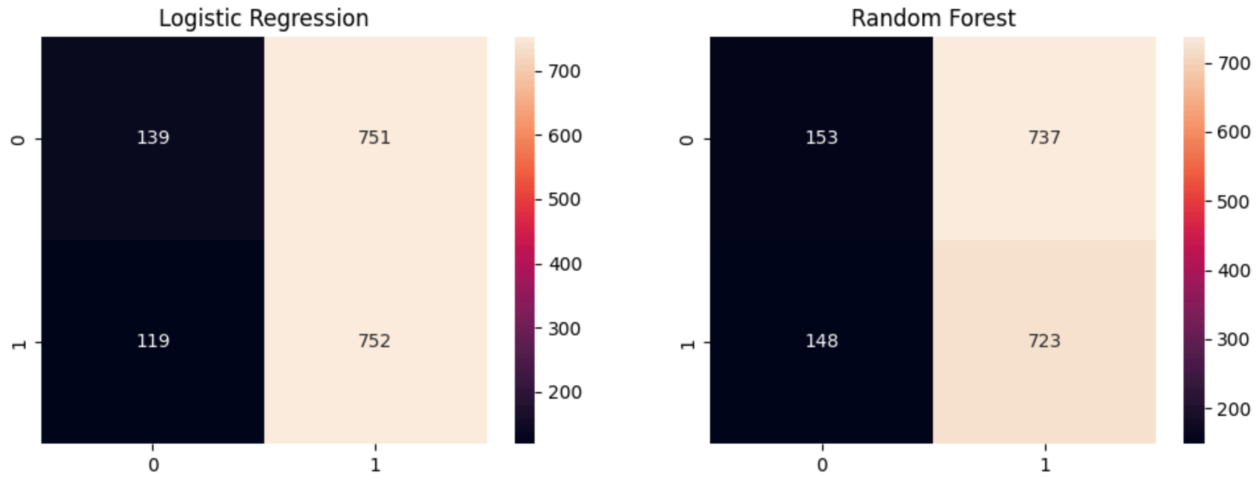
This section presents the final outputs from the machine learning analysis including model performance comparison, classification diagnostics, feature importance and clustering results.
The purpose of this section is to evaluate how different models perform on the same dataset and to understand where predictions

succeed or fail and summarize how banking stocks are distributed across the identified behavioral patterns.
These results provide transparency into the strengths and limitations of the models and help interpret the role of different financial indicators in the analysis.

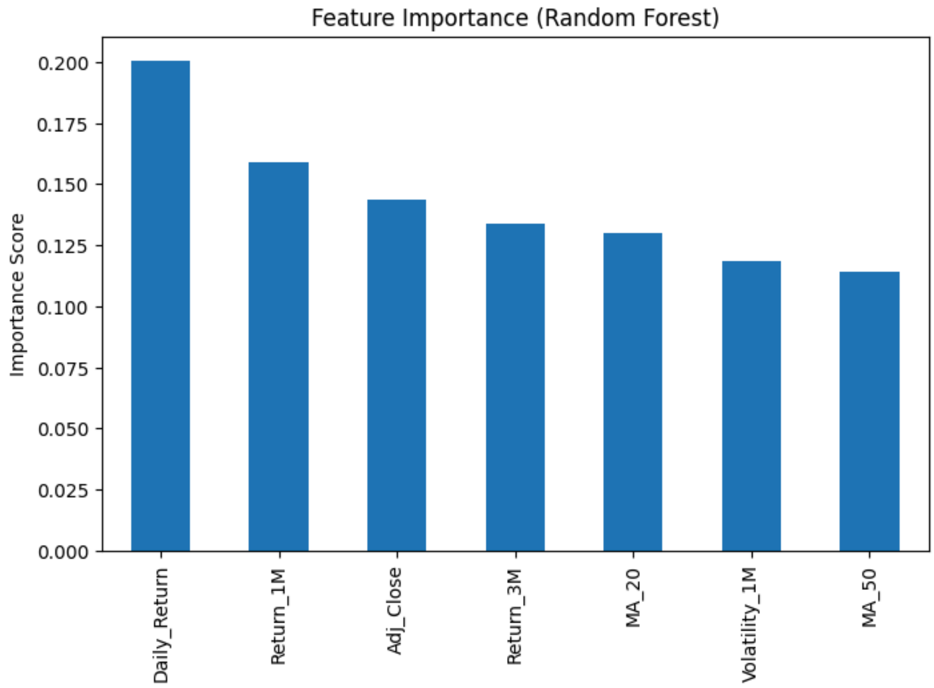
```
model_comparison = pd.DataFrame({
    'Model': ['Logistic Regression', 'Random Forest'],
    'Accuracy': [
        accuracy_score(y_test, y_pred_log),
        accuracy_score(y_test, y_pred_rf)
    ]
})

model_comparison
```

	Model	Accuracy
0	Logistic Regression	0.505963
1	Random Forest	0.497445

```
import seaborn as sns
import matplotlib.pyplot as plt

fig, axes = plt.subplots(1, 2, figsize=(12, 4))

sns.heatmap(confusion_matrix(y_test, y_pred_log),
            annot=True, fmt='d', ax=axes[0])
axes[0].set_title('Logistic Regression')

sns.heatmap(confusion_matrix(y_test, y_pred_rf),
            annot=True, fmt='d', ax=axes[1])
axes[1].set_title('Random Forest')

plt.show()
```




```
plt.figure(figsize=(8,5))
feature_importance.plot(kind='bar')
plt.title('Feature Importance (Random Forest)')
plt.ylabel('Importance Score')
plt.show()
```




```
cluster_distribution = (
    features_clean
    .groupby(['Ticker', 'Cluster'])
    .size()
    .unstack(fill_value=0)
)

cluster_distribution
```

Cluster Ticker	0	1	2
AXISBANK.NS	0	863	311
HDFCBANK.NS	0	1016	158
ICICIBANK.NS	0	901	273
KOTAKBANK.NS	1150	0	24
SBIN.NS	0	713	461

```
final_cluster_summary = features_clean.groupby('Cluster')[
    ['Return_1M', 'Return_3M', 'Volatility_1M']
].mean()

final_cluster_summary
```

Cluster	Return_1M	Return_3M	Volatility_1M
0	0.000251	0.000424	0.014566
1	0.000022	0.000417	0.013238
2	0.004147	0.003038	0.022051

```
features_clean.to_csv('final_ml_dataset.csv', index=False)
model_comparison.to_csv('model_comparison.csv', index=False)
final_cluster_summary.to_csv('cluster_summary.csv')
```

```
print("Final dataset shape:", features_clean.shape)
print("Train size:", X_train.shape)
print("Test size:", X_test.shape)
```

```
Final dataset shape: (5870, 11)
Train size: (4109, 7)
Test size: (1761, 7)
```

Double-click (or enter) to edit

Limitations

This analysis is based primarily on historical price data and publicly available financial metrics and does not incorporate macroeconomic variables such as interest rate movements, inflation, or regulatory changes that can significantly impact banking stocks.

Additionally, while machine learning techniques were used to explore behavioral patterns and test predictability, their effectiveness is inherently limited by market efficiency, particularly in short-term return forecasting.

As a result, the findings should be interpreted as analytical insights rather than actionable trading signals.

Closing Remarks & Key Takeaways

Financial Insights:
The analysis highlights meaningful differences in risk-adjusted performance and valuation across major Indian banking stocks. Metrics such as volatility, Sharpe ratio and ROE help explain why certain banks command valuation premiums while others trade at discounts.

Behavioral Patterns:
Machine learning-based analysis revealed distinct risk - return regimes within the banking sector, indicating that banks transition between stable, transitional and higher-risk phases depending on market conditions rather than exhibiting static behavior.

Predictability Assessment:
The supervised learning results indicate limited short-term return predictability, reinforcing the idea that banking stocks largely reflect available information in prices, consistent with efficient market behavior.