FINANCE AND RISK ANALYTICS

CREDIT RISK & MARKET RISK

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PART A

Context

In the realm of modern finance, businesses encounter the perpetual challenge of managing debt obligations effectively to maintain a favourable credit standing and foster sustainable growth. Investors keenly scrutinize companies capable of navigating financial complexities while ensuring stability and profitability. A pivotal instrument in this evaluation process is the balance sheet, which provides a comprehensive overview of a company's assets, liabilities, and shareholder equity, offering insights into its financial health and operational efficiency. In this context, leveraging available financial data, particularly from preceding fiscal periods, becomes imperative for informed decision-making and strategic planning.

Objective

A group of venture capitalists want to develop a Financial Health Assessment Tool. With the help of the tool, it endeavors to empower businesses and investors with a robust mechanism for evaluating the financial well-being and creditworthiness of companies. By harnessing machine learning techniques, they aim to analyze historical financial statements and extract pertinent insights to facilitate informed decision-making via the tool. Specifically, they foresee facilitating the following with the help of the tool:

1. Debt Management Analysis: Identify patterns and trends in debt management practices to assess the ability of businesses to fulfill financial obligations promptly and efficiently, and identify potential cases of default.
2. Credit Risk Evaluation: Evaluate credit risk exposure by analyzing liquidity ratios, debt-to-equity ratios, and other key financial indicators to ascertain the likelihood of default and inform investment decisions.

They have hired you as a data scientist and provided you with the financial metrics of different companies. The task is to analyze the data provided and develop a predictive model leveraging machine learning techniques to identify whether a given company will be tagged as a defaulter in terms of net worth next year. The predictive model will help the organization anticipate potential challenges with the financial performance of the companies and enable proactive risk mitigation strategies.

Data Dictionary

The data consists of financial metrics from the balance sheets of different companies. The detailed data dictionary is given below.

- Networth Next Year: Net worth of the customer in the next year
- Total assets: Total assets of customer
- Net worth: Net worth of the customer of the present year
- Total income: Total income of the customer
- Change in stock: Difference between the current value of the stock and the value of stock in the last trading day
- Total expenses: Total expenses done by the customer
- Profit after tax: Profit after tax deduction
- PBDITA: Profit before depreciation, income tax, and amortization
- PBT: Profit before tax deduction
- Cash profit: Total Cash profit
- PBDITA as % of total income: PBDITA / Total income
- PBT as % of total income: PBT / Total income

- PAT as % of total income: PAT / Total income
- Cash profit as % of total income: Cash Profit / Total income
- PAT as % of net worth: PAT / Net worth
- Sales: Sales done by the customer
- Income from financial services: Income from financial services
- Other income: Income from other sources
- Total capital: Total capital of the customer
- Reserves and funds: Total reserves and funds of the customer
- Borrowings: Total amount borrowed by the customer
- Current liabilities & provisions: current liabilities of the customer
- Deferred tax liability: Future income tax customer will pay because of the current transaction
- Shareholders funds: Amount of equity in a company which belongs to shareholders
- Cumulative retained profits: Total cumulative profit retained by customer
- Capital employed: Current asset minus current liabilities
- TOL/TNW: Total liabilities of the customer divided by Total net worth
- Total term liabilities / tangible net worth: Short + long term liabilities divided by tangible net worth
- Contingent liabilities / Net worth (%): Contingent liabilities / Net worth
- Contingent liabilities: Liabilities because of uncertain events
- Net fixed assets: The purchase price of all fixed assets
- Investments: Total invested amount
- Current assets: Assets that are expected to be converted to cash within a year
- Net working capital: Difference between the current liabilities and current assets
- Quick ratio (times): Total cash divided by current liabilities
- Current ratio (times): Current assets divided by current liabilities
- Debt to equity ratio (times): Total liabilities divided by its shareholder equity
- Cash to current liabilities (times): Total liquid cash divided by current liabilities
- Cash to average cost of sales per day: Total cash divided by the average cost of the sales
- Creditors turnover: Net credit purchase divided by average trade creditors
- Debtors turnover: Net credit sales divided by average accounts receivable
- Finished goods turnover: Annual sales divided by average inventory
- WIP turnover: The cost of goods sold for a period divided by the average inventory for that period
- Raw material turnover: Cost of goods sold is divided by the average inventory for the same period
- Shares outstanding: Number of issued shares minus the number of shares held in the company
- Equity face value: cost of the equity at the time of issuing
- EPS: Net income divided by the total number of outstanding share
- Adjusted EPS: Adjusted net earnings divided by the weighted average number of common shares outstanding on a diluted basis during the plan year
- Total liabilities: Sum of all types of liabilities
- PE on BSE: Company's current stock price divided by its earnings per share

EDA

	Num	Networth_Next_Year	Total_assets	Net_worth	Total_income	Change_in_stock	Total_expenses	Profit_after_tax	PBDITA	PBT	...	Debtors_turnover
0	1	395.3	827.6	336.5	534.1	13.5	508.7	38.9	124.4	64.6	...	5.65
1	2	36.2	67.7	24.3	137.9	-3.7	131.0	3.2	5.5	1.0	...	NaN
2	3	84.0	238.4	78.9	331.2	-18.1	309.2	3.9	25.8	10.5	...	2.51
3	4	2041.4	6883.5	1443.3	8448.5	212.2	8482.4	178.3	418.4	185.1	...	1.91
4	5	41.8	90.9	47.0	388.6	3.4	392.7	-0.7	7.2	-0.6	...	68.00

5 rows × 51 columns

Figure 1: Sample dataset

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4256 entries, 0 to 4255
Data columns (total 51 columns):
 #   Column                                   Non-Null Count  Dtype  
---  ------                                   --------------  -----  
 0   Num                                      4256 non-null   int64  
 1   Networth_Next_Year                       4256 non-null   float64
 2   Total_assets                             4256 non-null   float64
 3   Net_worth                                4256 non-null   float64
 4   Total_income                             4025 non-null   float64
 5   Change_in_stock                          3706 non-null   float64
 6   Total_expenses                           4091 non-null   float64
 7   Profit_after_tax                         4102 non-null   float64
 8   PBDITA                                   4102 non-null   float64
 9   PBT                                      4102 non-null   float64
 10  Cash_profit                              4102 non-null   float64
 11  PBDITA_as_perc_of_total_income           4177 non-null   float64
 12  PBT_as_perc_of_total_income              4177 non-null   float64
 13  PAT_as_perc_of_total_income              4177 non-null   float64
 14  Cash_profit_as_perc_of_total_income      4177 non-null   float64
 15  PAT_as_perc_of_net_worth                 4256 non-null   float64
 16  Sales                                    3951 non-null   float64
 17  Income_from_fincial_services             3145 non-null   float64
 18  Other_income                             2700 non-null   float64
 19  Total_capital                            4251 non-null   float64
 20  Reserves_and_funds                       4158 non-null   float64
 21  Borrowings                               3825 non-null   float64
 22  Current_liabilities_&_provisions         4146 non-null   float64
 23  Deferred_tax_liability                   2887 non-null   float64
 24  Shareholders_funds                       4256 non-null   float64
 25  Cumulative_retained_profits              4211 non-null   float64
 26  Capital_employed                         4256 non-null   float64
 27  TOL_to_TNW                               4256 non-null   float64
 28  Total_term_liabilities__to__tangible_net_worth  4256 non-null   float64
 29  Contingent_liabilities__to__Net_worth_perc      4256 non-null   float64
 30  Contingent_liabilities                   2854 non-null   float64
 31  Net_fixed_assets                         4124 non-null   float64
 32  Investments                              2541 non-null   float64
 33  Current_assets                           4176 non-null   float64
 34  Net_working_capital                      4219 non-null   float64
 35  Quick_ratio_times                        4151 non-null   float64
 36  Current_ratio_times                      4151 non-null   float64
 37  Debt_to_equity_ratio_times               4256 non-null   float64
 38  Cash_to_current_liabilities_times        4151 non-null   float64
 39  Cash_to_average_cost_of_sales_per_day    4156 non-null   float64
 40  Creditors_turnover                       3865 non-null   float64
 41  Debtors_turnover                         3871 non-null   float64
 42  Finished_goods_turnover                  3382 non-null   float64
 43  WIP_turnover                             3492 non-null   float64
 44  Raw_material_turnover                    3828 non-null   float64
 45  Shares_outstanding                       3446 non-null   float64
 46  Equity_face_value                        3446 non-null   float64
 47  EPS                                      4256 non-null   float64
 48  Adjusted_EPS                             4256 non-null   float64
 49  Total_liabilities                        4256 non-null   float64
 50  PE_on_BSE                                1629 non-null   float64
dtypes: float64(50), int64(1)
memory usage: 1.7 MB
```

Figure 2: Datatypes

	count	mean	std	min	25%	50%	75%	max
Num	4256.00	2128.50	1228.75	1.00	1064.75	2128.50	3192.25	4256.00
Networth_Next_Year	4256.00	1344.74	15936.74	-74265.60	3.98	72.10	330.82	805773.40
Total_assets	4256.00	3573.62	30074.44	0.10	91.30	315.50	1120.80	1176509.20
Net_worth	4256.00	1351.95	12961.31	0.00	31.48	104.80	389.85	613151.60
Total_income	4025.00	4688.19	53918.95	0.00	107.10	455.10	1485.00	2442828.20
Change_in_stock	3706.00	43.70	436.92	-3029.40	-1.80	1.60	18.40	14185.50
Total_expenses	4091.00	4356.30	51398.09	-0.10	96.80	426.80	1395.70	2366035.30
Profit_after_tax	4102.00	295.05	3079.90	-3908.30	0.50	9.00	53.30	119439.10
PBDITA	4102.00	605.94	5646.23	-440.70	6.93	36.90	158.70	208576.50
PBT	4102.00	410.26	4217.42	-3894.80	0.80	12.60	74.17	145292.60
Cash_profit	4102.00	408.27	4143.93	-2245.70	2.90	19.40	96.25	176911.80
PBDITA_as_perc_of_total_income	4177.00	3.18	172.26	-6400.00	4.97	9.68	16.47	100.00
PBT_as_perc_of_total_income	4177.00	-18.20	419.91	-21340.00	0.56	3.34	8.94	100.00
PAT_as_perc_of_total_income	4177.00	-20.03	423.58	-21340.00	0.35	2.37	6.42	150.00
Cash_profit_as_perc_of_total_income	4177.00	-9.02	299.96	-15020.00	2.00	5.66	10.73	100.00
PAT_as_perc_of_net_worth	4256.00	10.17	61.53	-748.72	0.00	8.04	20.20	2466.67
Sales	3951.00	4645.68	53080.90	0.10	113.35	468.60	1481.20	2384984.40
Income_from_fincial_services	3145.00	81.36	1042.76	0.00	0.50	1.90	9.80	51938.20
Other_income	2700.00	55.95	1178.42	0.00	0.40	1.50	6.20	42856.70
Total_capital	4251.00	224.56	1684.95	0.10	13.20	42.60	103.15	78273.20
Reserves_and_funds	4158.00	1210.56	12816.23	-6525.90	5.30	55.15	282.52	625137.80

Figure 3: Descriptive stats 1

Borrowings	3825.00	1176.25	8581.25	0.10	24.40	99.80	358.30	278257.30
Current_liabilities_&_provisions	4146.00	960.63	9140.54	0.10	17.50	70.30	265.92	352240.30
Deferred_tax_liability	2887.00	234.50	2106.25	0.10	3.20	13.50	51.30	72796.60
Shareholders_funds	4256.00	1376.49	13010.69	0.00	32.30	107.60	408.90	613151.60
Cumulative_retained_profits	4211.00	937.18	9853.10	-6534.30	1.10	37.40	206.20	390133.80
Capital_employed	4256.00	2433.62	20496.40	0.00	61.30	221.20	790.30	891408.90
TOL_to_TNW	4256.00	4.03	20.88	-350.48	0.60	1.42	2.83	473.00
Total_term_liabilities__to__tangible_net_worth	4256.00	1.85	15.88	-325.60	0.05	0.34	1.00	456.00
Contingent_liabilities__to__Net_worth_perc	4256.00	55.71	369.17	0.00	0.00	5.36	31.01	14704.27
Contingent_liabilities	2854.00	948.55	12056.74	0.10	6.00	37.85	195.32	559506.80
Net_fixed_assets	4124.00	1209.49	12502.40	0.00	26.20	93.85	352.82	636604.60
Investments	2541.00	721.87	6793.86	0.00	1.00	8.20	63.80	199978.60
Current_assets	4176.00	1350.36	10155.57	0.10	36.60	148.35	515.00	354815.20
Net_working_capital	4219.00	162.87	3182.03	-63839.00	-1.10	16.70	86.50	85782.80
Quick_ratio_times	4151.00	1.50	9.33	0.00	0.41	0.67	1.03	341.00
Current_ratio_times	4151.00	2.26	12.48	0.00	0.93	1.23	1.72	505.00
Debt_to_equity_ratio_times	4256.00	2.87	15.60	0.00	0.22	0.79	1.75	456.00
Cash_to_current_liabilities_times	4151.00	0.53	4.80	0.00	0.02	0.07	0.19	165.00
Cash_to_average_cost_of_sales_per_day	4156.00	145.16	2521.99	0.00	2.88	8.04	21.97	128040.76
Creditors_turnover	3865.00	16.81	75.67	0.00	3.72	6.17	11.69	2401.00
Debtors_turnover	3871.00	17.93	90.16	0.00	3.81	6.47	11.85	3135.20
Finished_goods_turnover	3382.00	84.37	562.64	-0.09	8.19	17.32	40.01	17947.60
WIP_turnover	3492.00	28.68	169.65	-0.18	5.10	9.86	20.24	5651.40
Raw_material_turnover	3828.00	17.73	343.13	-2.00	3.02	6.41	11.82	21092.00
Shares_outstanding	3446.00	23764909.56	170979041.33	-2147483647.00	1308382.50	4750000.00	10906020.00	4130400545.00
Equity_face_value	3446.00	-1094.83	34101.36	-999998.90	10.00	10.00	10.00	100000.00
EPS	4256.00	-196.22	13061.95	-843181.82	0.00	1.49	10.00	34522.53
Adjusted_EPS	4256.00	-197.53	13061.93	-843181.82	0.00	1.24	7.62	34522.53
Total_liabilities	4256.00	3573.62	30074.44	0.10	91.30	315.50	1120.80	1176509.20
PE_on_BSE	1629.00	55.46	1304.45	-1116.64	2.97	8.69	17.00	51002.74

Figure 4: Descriptive stats 2

- Number of rows: 4256
- Number of columns: 51
- The dataset only contains numerical variables.
- All variables are float, so there are no special characters, etc.
- The equity face value is a constant value for all rows and is not a good predictor variable, hence it can be excluded from the study.
- Approximately 21% of the companies are in default.
- Total number of null values in the dataset: 17778
- Total number of values in the dataset: 221312
- Percentage of missing values in the dataset: 8.033003181029496%
- 8% of the total dataset has null values.
- Total percentage of null values and outliers: 16.122487709658763%
- The default variable, based on the worth next year, is no longer useful for predictions.

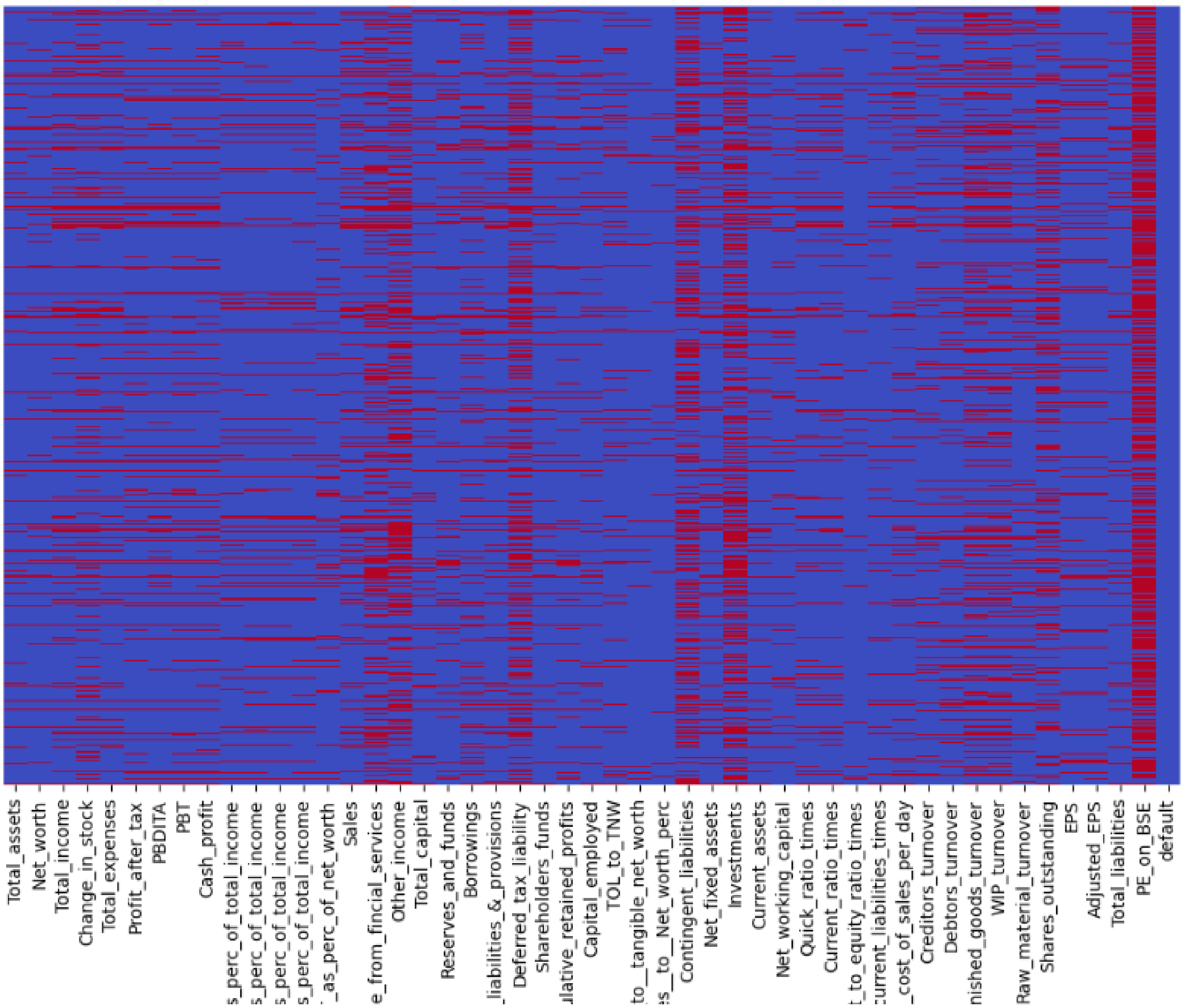

Figure 5: Heatmap of null values

Filtering the data with more than 90% of data at the row level:

- The total number of rows has decreased from 4200 to 2285.

- The complete dataset contains approximately 16% of null and outlier values combined.

- The dataset does not provide highly informative information.

  - (Income_from_fincial_services','Deferred_tax_liability','Contingent_liabilities','Other_income','Investments','PE_on_BSE) Columns have more than 30% missing data and was removed.

Univariate and Bivariate Analysis

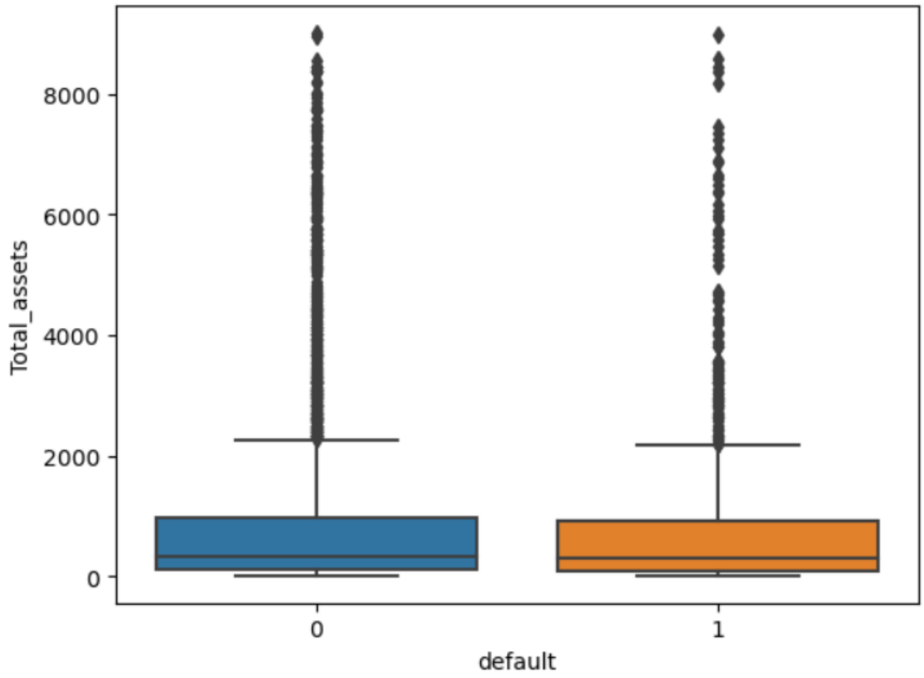

Figure 6: Boxplot for total_assets

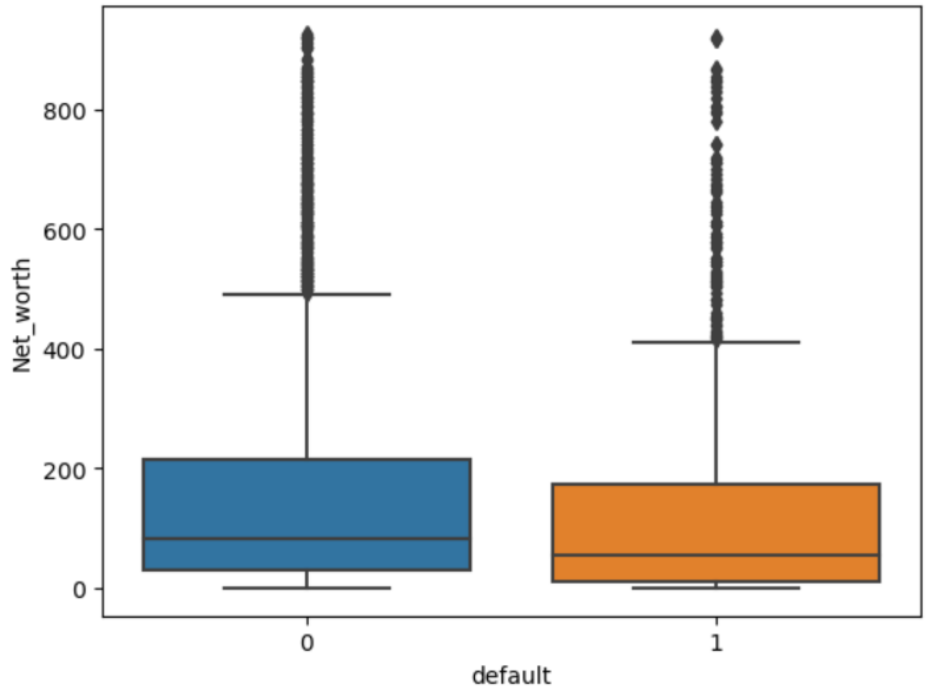

Figure 7: Boxplot for Networth

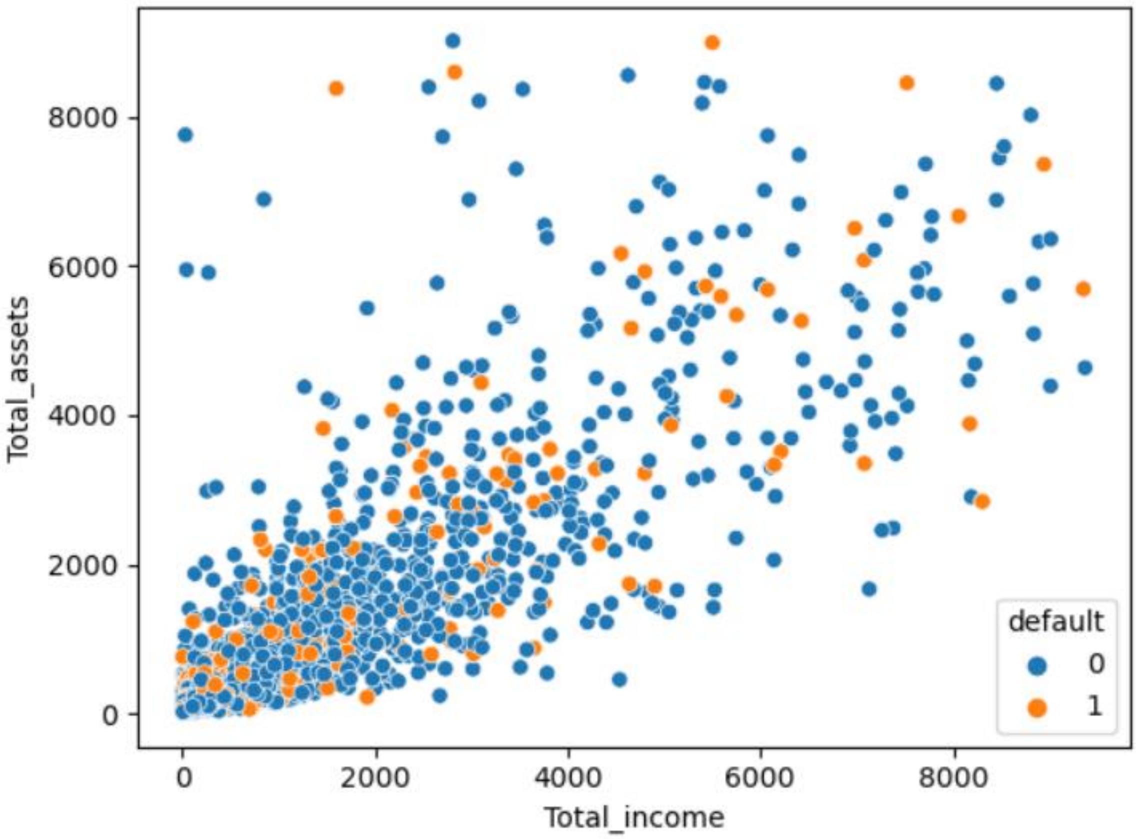

Figure 8: Scatterplot between total assets and total income

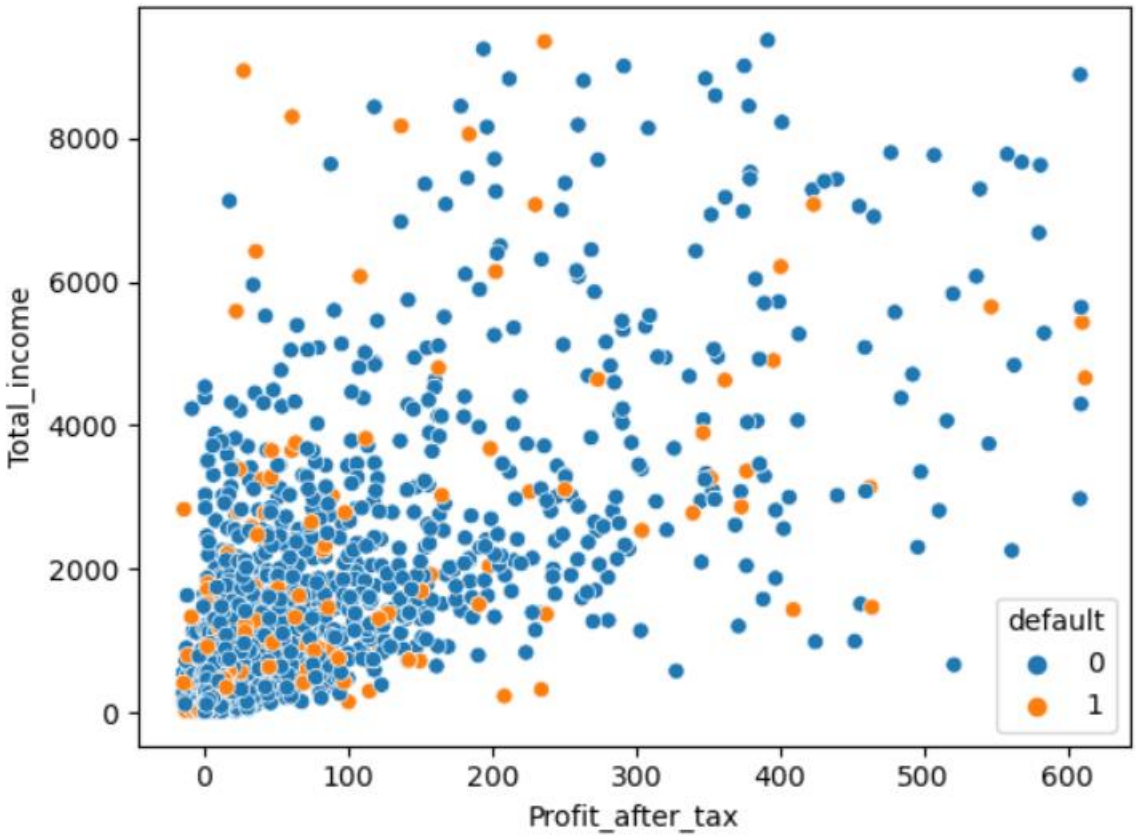

Figure 9: Scatterplot between total income and PAT

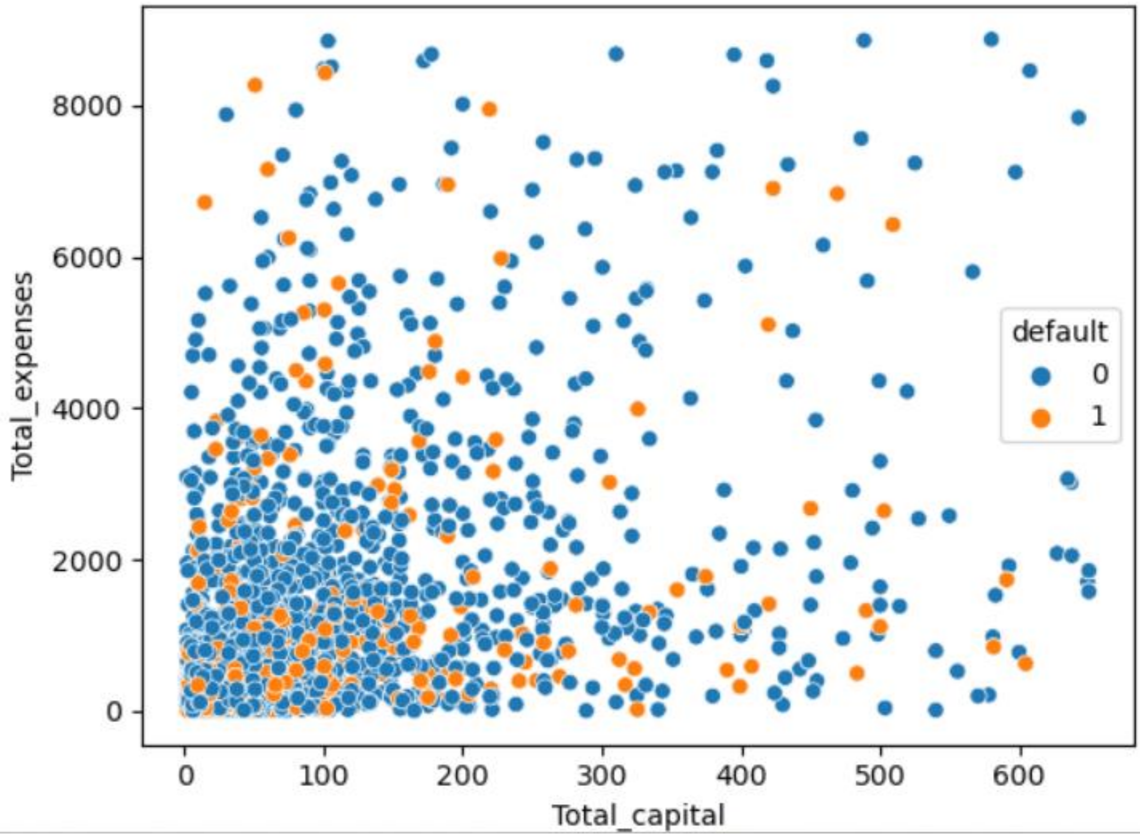

Figure 10: Scatterplot between total capital and total expenses

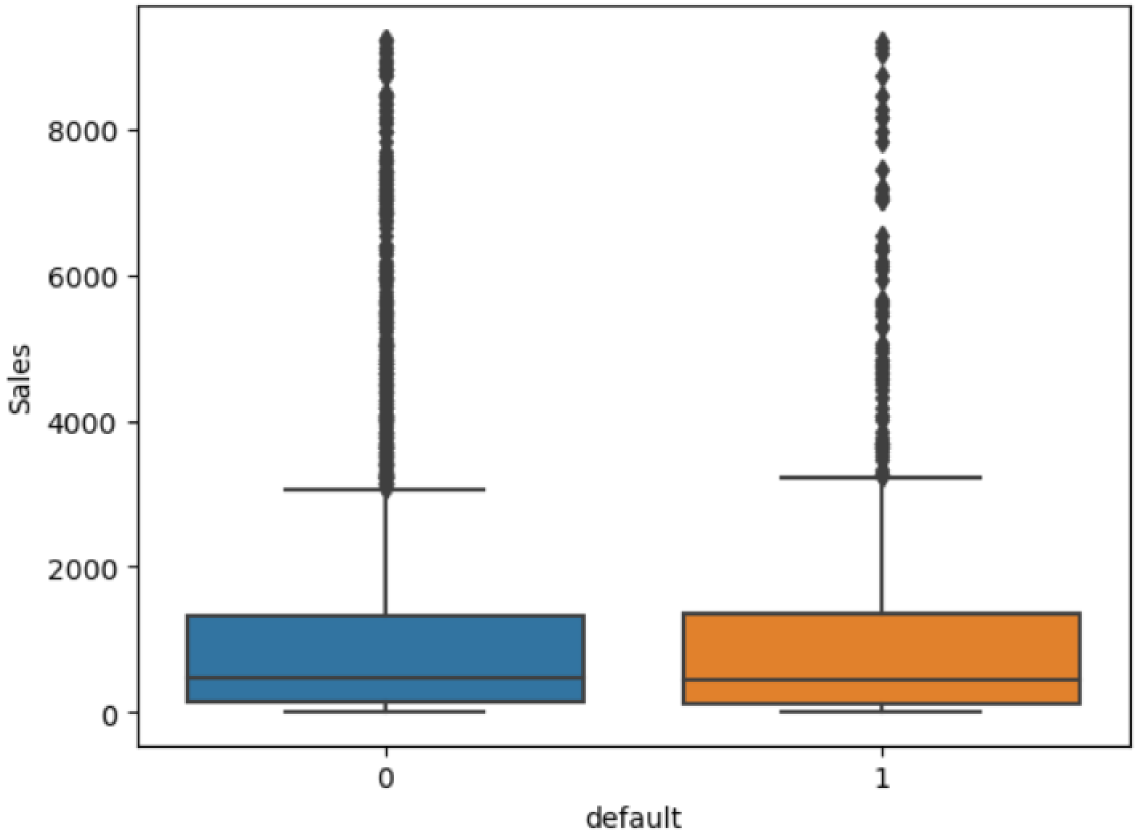

Figure 11: Boxplot between default and sales

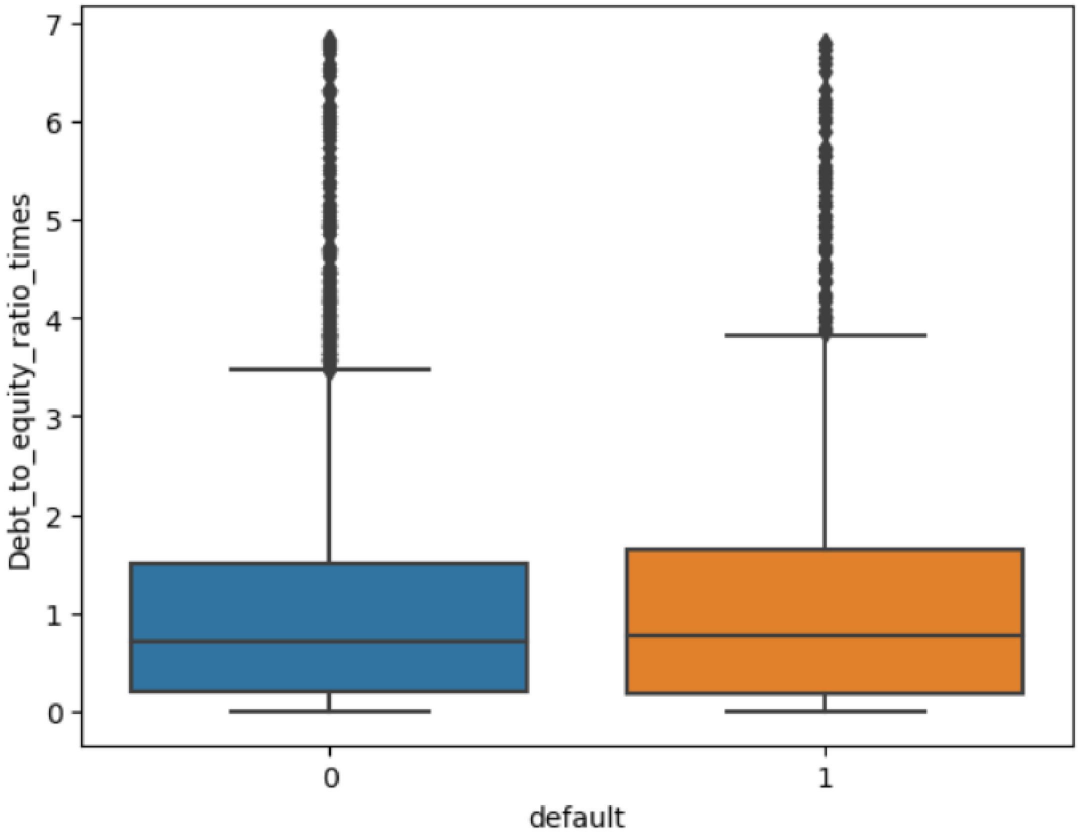

Figure 12: Boxplot between Debt-to-equity ratio and default

- The total assets do not seem to have a significant impact on defaulters.
- Even though the overall net worth of the defaulters is less compared to non-defaulters, the difference is not significant.
- An upward trend is visible, indicating that as the total income increases, the total assets also increase.
- The maximum number of companies falls in the range of 0-1500 in both total income and total assets.
- Most companies lie within the range of -25 to 50 units.
- Up to 25 units, companies with lower total income have lower profit after tax, and after 25 units, there is an upward trend where the income increases and the total profit after tax also increases.
- Companies with less total capital are likely to have higher expenses.
- Based on the analysis, no significant difference between defaulters and non-defaulters following a specific trend or pattern was observed.
- No significant predictor variable was identified.

Model Building

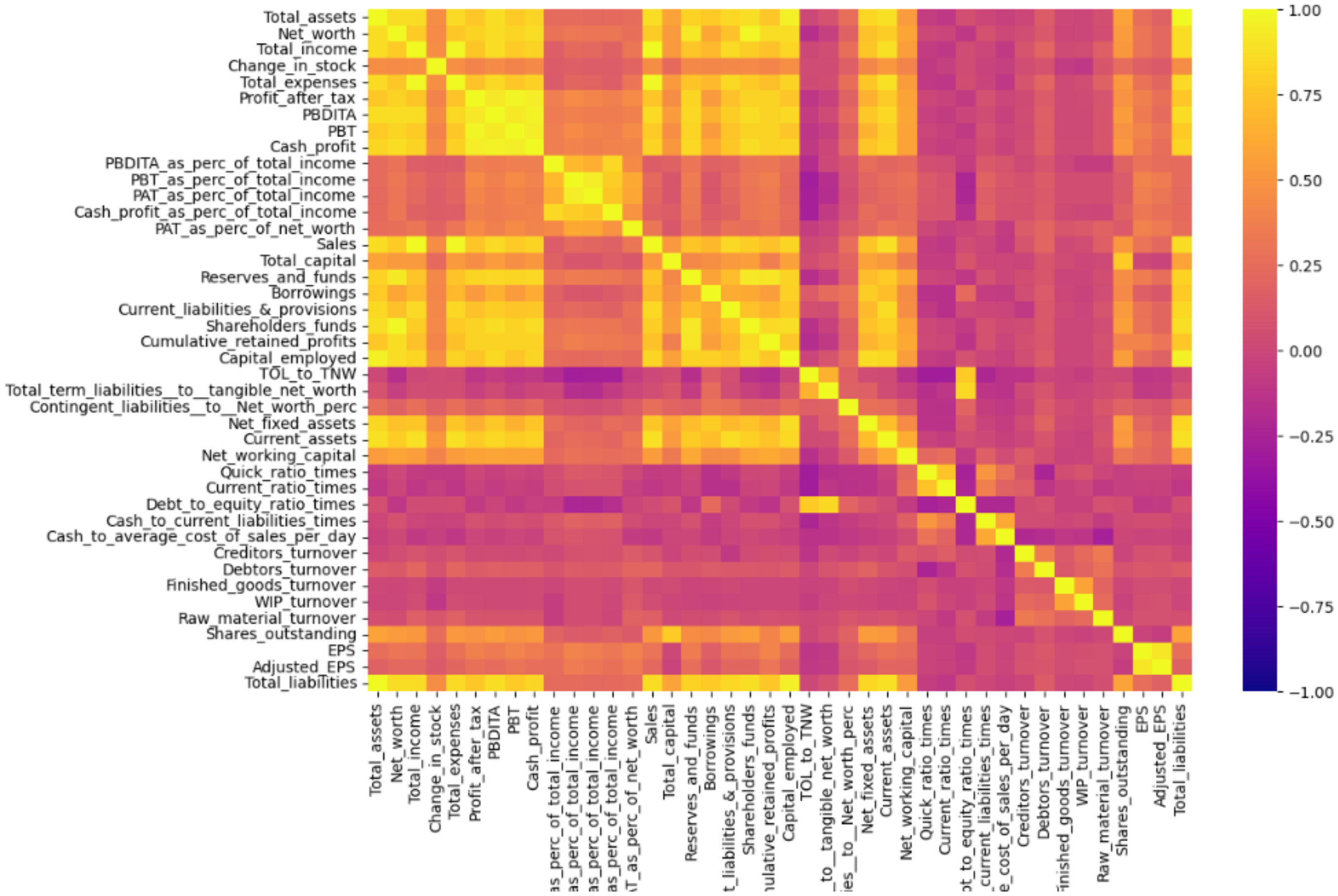

Figure 13: Correlation between independent variables

- Since we can see a lot of positive correlation, there is a high multicollinearity visible here hence we have to use VIF to reduce the number of features.

Model 1- Logistic Regression

	variables	VIF
24	Contingent_liabilities__to__Net_worth_perc	1.196447
37	Raw_material_turnover	1.407050
33	Creditors_turnover	1.505992
35	Finished_goods_turnover	1.562286
3	Change_in_stock	1.573576
34	Debtors_turnover	1.576679
36	WIP_turnover	1.701949
32	Cash_to_average_cost_of_sales_per_day	1.789320
31	Cash_to_current_liabilities_times	2.030409
13	PAT_as_perc_of_net_worth	2.148994
27	Net_working_capital	2.312654
29	Current_ratio_times	2.727608
38	Shares_outstanding	2.905613
15	Total_capital	2.910851
22	TOL_to_TNW	3.075824
28	Quick_ratio_times	3.134745
9	PBDITA_as_perc_of_total_income	3.614330
23	Total_term_liabilities__to__tangible_net_worth	4.054380
12	Cash_profit_as_perc_of_total_income	4.995065
17	Borrowings	5.203334
30	Debt_to_equity_ratio_times	5.587659
25	Net_fixed_assets	5.773034

Figure 14: VIF data frame

- Here, we can see that the VIF is high for most of the variables and we are going to exclude those variables having a VIF greater than 5.

```
Logistic Regression Confusion Matrix:
[[1014    2]
 [ 261    0]]
Logistic Regression Classification report:
              precision    recall  f1-score   support

         0.0       0.80      1.00      0.89      1016
         1.0       0.00      0.00      0.00       261

    accuracy                           0.79      1277
   macro avg       0.40      0.50      0.44      1277
weighted avg       0.63      0.79      0.70      1277
```

Figure 15: Model 1- confusion matrix and classification report

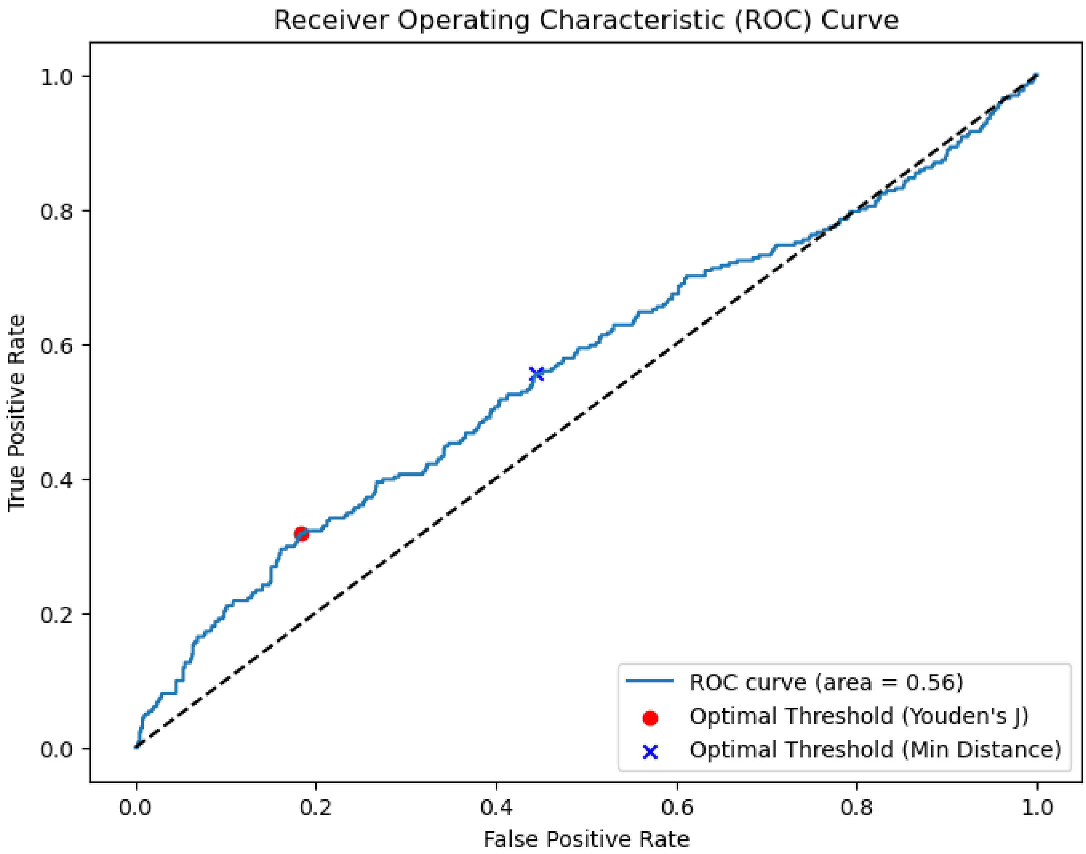

Figure 16: Model 1- ROC curve

Optimal Threshold (Youden's J): 0.2548562610208426

Optimal Threshold (Min Distance): 0.21198159864695984

- Since we saw a very poor recall value for the model we will balance the data before fitting the model.

Model 2- Logistic Regression using SMOTE

	precision	recall	f1-score	support
0	0.78	0.01	0.01	1029
1	0.19	0.99	0.32	248
accuracy			0.20	1277
macro avg	0.49	0.50	0.17	1277
weighted avg	0.66	0.20	0.07	1277

Figure 17: Model 2- Classification report

- Finally, we are able to achieve an excellent recall value with some overfitting.
- Considering the opportunities such as outliers, missing values and correlated features this is a fair model.
- Even though the recall value is exceptional, the model has very low precision and accuracy.
- Since our major requirement is to predict the defaulters, this model has done an exceptional job.

Model 3- Random Forest

```
Confusion Matrix:
[[876 153]
 [224  24]]
Classification Report:
              precision    recall  f1-score   support

           0       0.80      0.85      0.82      1029
           1       0.14      0.10      0.11       248

    accuracy                           0.70      1277
   macro avg       0.47      0.47      0.47      1277
weighted avg       0.67      0.70      0.69      1277
```

Figure 18: Model 3- confusion matrix and classification report

- The model shows a very poor performance hence we can proceed to hyperparameter tuning methods.

Model 4- Hyperparameter tuning GridsearchCV

```
Confusion Matrix:
[[1005   24]
 [ 228   20]]
Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.98      0.89      1029
           1       0.45      0.08      0.14       248

    accuracy                           0.80      1277
   macro avg       0.63      0.53      0.51      1277
weighted avg       0.75      0.80      0.74      1277
```

Figure 19: Model 4- confusion matrix and classification report

- The model has very poor recall value for predicting defaulters hence we cannot proceed with this model.

Final Model

- Out of the 4 models considered, the logistic regression model, after balancing the training data, is the best model to proceed with for the following reasons:

- The model exhibits an outstanding recall value of 99%.
- It excels at identifying defaulters, but performs poorly in identifying non-defaulters.

- Given that the primary goal is to minimize credit risk, this model effectively helps the industry identify potential defaulters, enabling them to avoid extending credit to such companies and ultimately reducing their credit risk.

	Feature	Coefficient
6	WIP_turnover	0.190075
5	Finished_goods_turnover	-0.184159
3	Creditors_turnover	-0.157833
10	Net_working_capital	0.151301
8	PAT_as_perc_of_net_worth	-0.097125
14	Total_capital	-0.083058
9	Cash_to_current_liabilities_times	-0.079641
2	Change_in_stock	-0.074257
7	Cash_to_average_cost_of_sales_per_day	-0.057136
11	Current_ratio_times	-0.053223
0	Contingent_liabilities__to__Net_worth_perc	-0.051087
12	Shares_outstanding	-0.044827
17	PBDITA_as_perc_of_total_income	-0.037438
18	Cash_profit_as_perc_of_total_income	0.032779
1	Raw_material_turnover	-0.029999
16	Total_term_liabilities__to__tangible_net_worth	-0.024928
15	Quick_ratio_times	0.020606
13	TOL_to_TNW	0.019197
4	Debtors_turnover	-0.011478

	Absolute Coefficient
6	0.190075
5	0.184159
3	0.157833
10	0.151301
8	0.097125
14	0.083058
9	0.079641
2	0.074257
7	0.057136
11	0.053223
0	0.051087

Figure 20: Feature importance

Inferences

Class Imbalance:

- The model shows a significant imbalance in class performance.
- Class 0 (majority class) has 1029 instances, while class 1 (minority class) has only 248 instances.

Precision, Recall, and F1-Score:

Class 0:

- Precision: The precision for class 0 is 0.78, indicating that 78% of the predicted class 0 instances are correct.
- Recall: The recall for class 0 is extremely low at 0.01, meaning that only 1% of the actual class 0 instances are correctly identified.

Class 1:

- Precision: The precision for class 1 is 0.19, indicating that 19% of the predicted class 1 instances are correct.
- Recall: The recall for class 1 is very high at 0.99, meaning that 99% of the actual class 1 instances are correctly identified.
- The overall accuracy of the model is 0.20, which is quite low and indicates poor model performance. This low accuracy is primarily due to the model's inability to correctly identify class 0 instances.
- The features with the highest absolute coefficient values are considered the most important for the model's predictions. Here are the top features and their respective coefficients:

1. WIP_turnover: Coefficient = 0.190075
2. Finished_goods_turnover: Coefficient = -0.184159
3. Creditors_turnover: Coefficient = -0.157833
4. Net_working_capital: Coefficient = 0.151301
5. PAT_as_perc_of_net_worth: Coefficient = -0.097125

Insights And Recommendations

1) High Recall for Loan Defaults (Class 1):

- The model's ability to correctly identify 99% of loan defaults (high recall) is crucial for risk management. This ensures that almost all potential defaulters are flagged for further investigation or preemptive action.

2) Feature Importance and Business Impact:

- ***WIP_turnover (Work-in-progress turnover):***

A positive coefficient suggests that higher WIP turnover is associated with an increased likelihood of loan default. This could indicate that businesses with high inventory turnover in progress might be at financial risk.

- ***Finished_goods_turnover:***

A negative coefficient indicates that higher turnover of finished goods is associated with a lower likelihood of default, suggesting that efficient sales and inventory management of finished goods are signs of financial health.

- ***Creditors_turnover:***

Negative coefficient implies that quicker payment of creditors is linked to a lower chance of default, highlighting the importance of managing payables efficiently.

- ***Net_working_capital:***

Positive coefficient suggests that higher net working capital is linked to an increased likelihood of default, possibly indicating over-leveraging or liquidity issues.

- ***PAT_as_perc_of_net_worth:***

Negative coefficient shows that higher profitability relative to net worth is associated with a lower likelihood of default, emphasizing the importance of profitability in maintaining financial stability.

- Focus on clients with high WIP turnover and low finished goods turnover, as these are indicative of higher default risk.
- Implement stricter credit policies or offer tailored financial products for businesses with high net working capital and low profitability ratios to mitigate risk.
- Encourage clients to improve their finished goods turnover by optimizing inventory management and sales processes.
- Advise clients to manage their payables more efficiently to improve creditor turnover, reducing the risk of cash flow issues.
- Provide financial advisory services to help businesses improve their profitability metrics, such as PAT as a percentage of net worth, which in turn reduces default risk.
- Offer liquidity solutions to businesses with high net working capital but facing potential liquidity issues to ensure they can meet their short-term obligations.

PART B

Context

Investors face market risk, arising from asset price fluctuations due to economic events, geopolitical developments, and investor sentiment changes. Understanding and analyzing this risk is crucial for informed decision-making and optimizing investment strategies.

Objective

The objective of this analysis is to conduct Market Risk Analysis on a portfolio of Indian stocks using Python. It uses historical stock price data to understand market volatility and riskiness. Using statistical measures like mean and standard deviation, investors gain a deeper understanding of individual stocks' performance and portfolio variability.

Through this analysis, investors can aim to achieve the following objectives:

- Risk Assessment: Analyze the historical volatility of individual stocks and the overall portfolio.
- Portfolio Optimization: Use Market Risk Analysis insights to enhance risk-adjusted returns.
- Performance Evaluation: Assess portfolio management strategies' effectiveness in mitigating market risk.
- Portfolio Performance Monitoring: Monitor portfolio performance over time and adjust as market conditions and risk preferences change.

Data Dictionary

The dataset contains weekly stock price data for 5 Indian stocks over an 8-year period. The dataset enables us to analyze the historical performance of individual stocks and the overall market dynamics.

	Date	ITC Limited	Bharti Airtel	Tata Motors	DLF Limited	Yes Bank
0	28-03-2016	217	316	386	114	173
1	04-04-2016	218	302	386	121	171
2	11-04-2016	215	308	374	120	171
3	18-04-2016	223	320	408	122	172
4	25-04-2016	214	319	418	122	175

Figure 21: Sample dataset

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Date           418 non-null    datetime64[ns]
 1   ITC_Limited    418 non-null    int64
 2   Bharti_Airtel  418 non-null    int64
 3   Tata_Motors    418 non-null    int64
 4   DLF_Limited    418 non-null    int64
 5   Yes_Bank       418 non-null    int64
dtypes: datetime64[ns](1), int64(5)
```

Figure 22: Datatypes

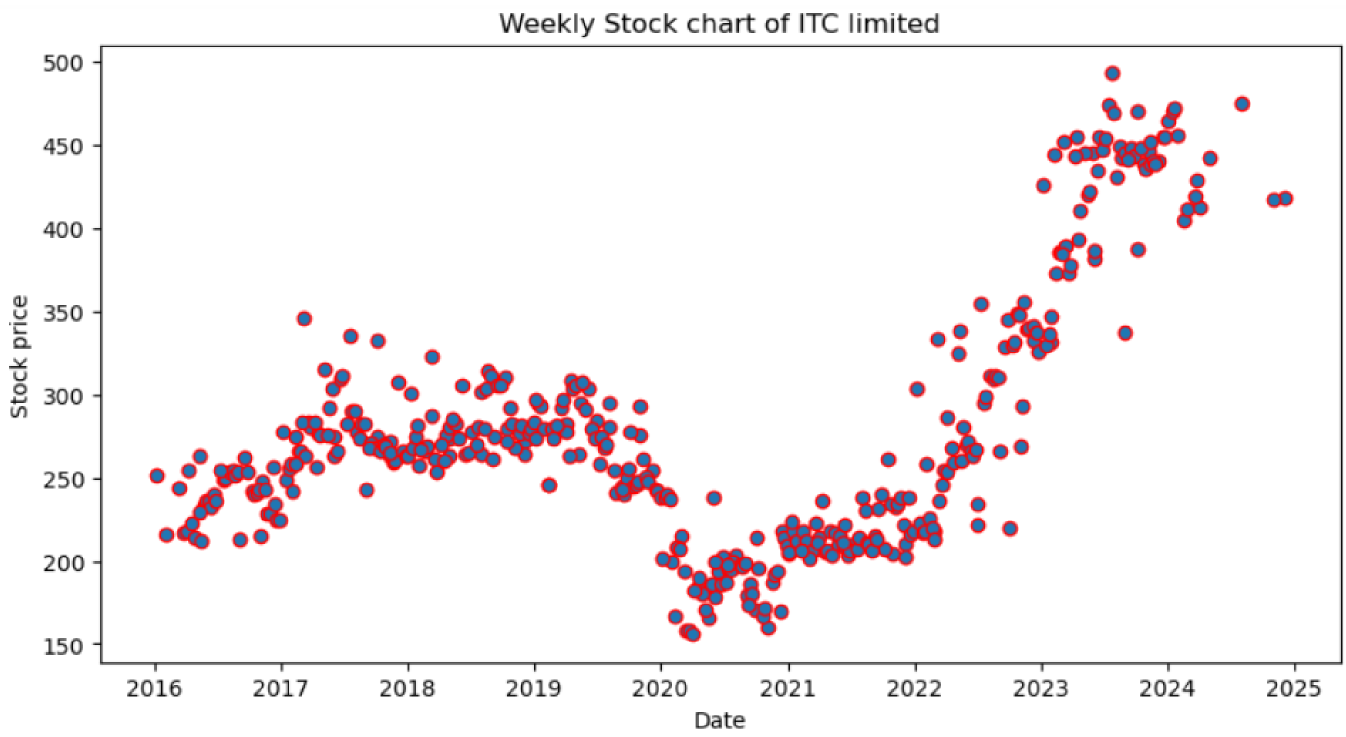

Figure 23: Weekly stock chart of ITC limited

- From 2016 to 2019, the stock price remained relatively stable, indicating a period of consolidation.
- Between 2019 and 2020, the stock price declined to 150.
- From 2020 to the present, the stock price has shown significant growth, reaching over 450.
- Currently, the stock is either consolidating or there could be a potential trend reversal.

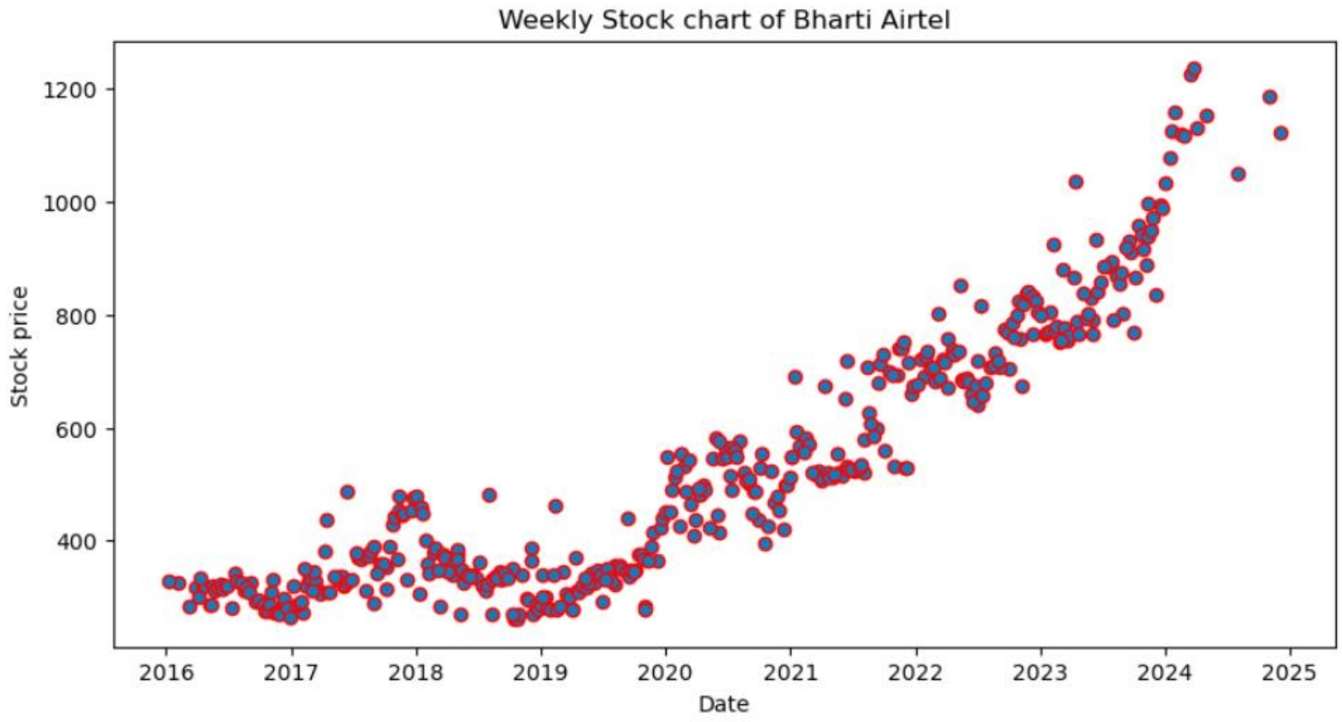

Figure 24: Weekly stock chart of Bharti Airtel

- From 2016 to 2020, the stock price remained relatively stable, indicating a period of consolidation.
- From 2020 to the present, the stock price has surged and currently stands at over 1200.
- The stock is currently following an uptrend.

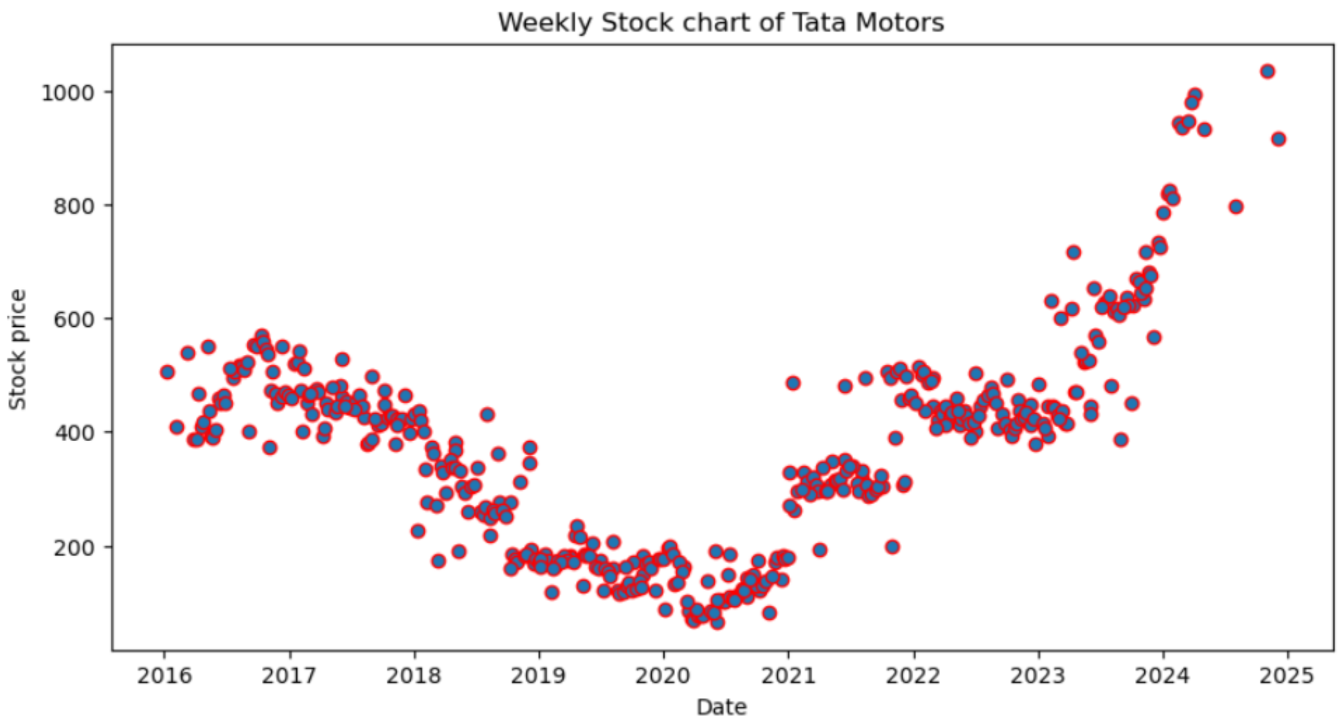

Figure 25: Weekly stock chart of Tata Motors

- From the year 2016-2020 the price reduced and came down less than 200.
- From 2020- till now the price of the stock has gained momentum and has reached more than 1000.
- A trend reversal is found after 2020 and the stock is following an uptrend.

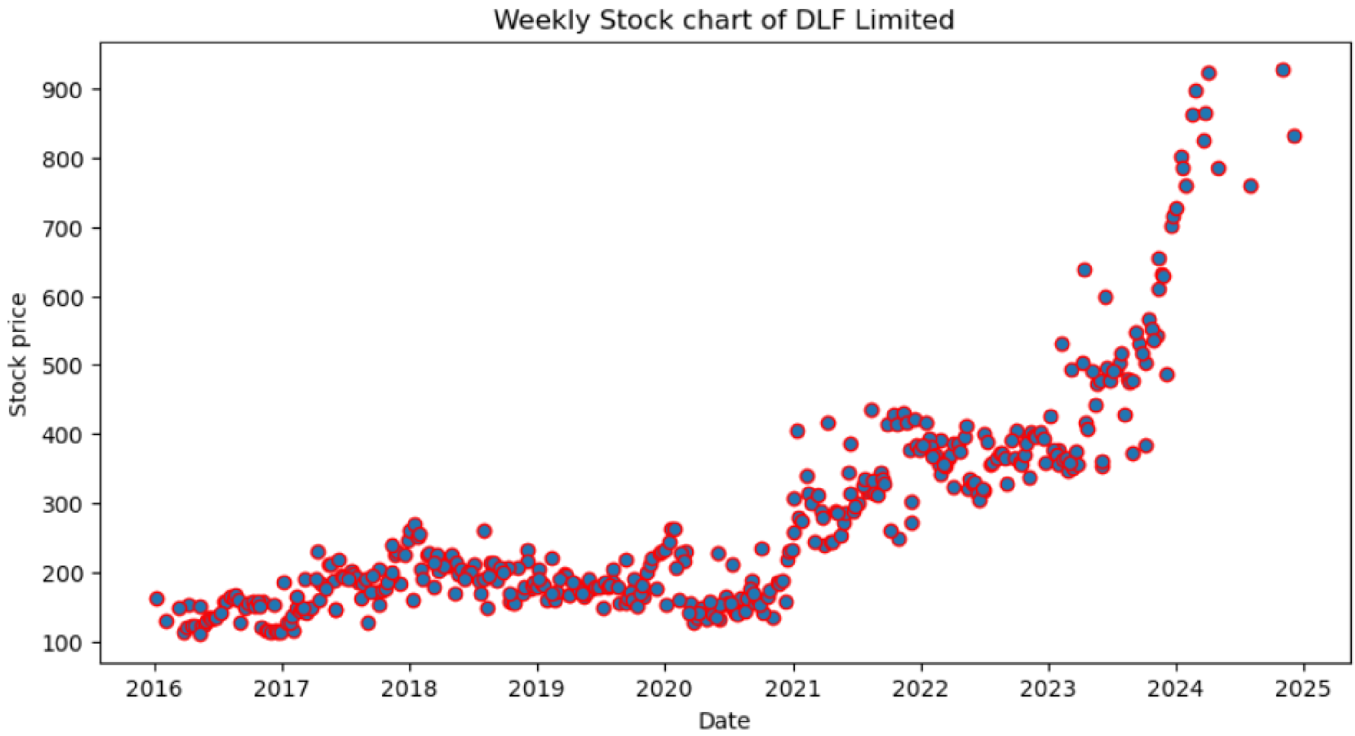

Figure 26: Weekly stock chart of DLF Limited

- From 2016 to 2021, the stock price remained relatively stable, indicating a period of consolidation.

- Since 2020, the stock price has surged and is now over 900.

- Currently, the stock is once again in a consolidation phase.

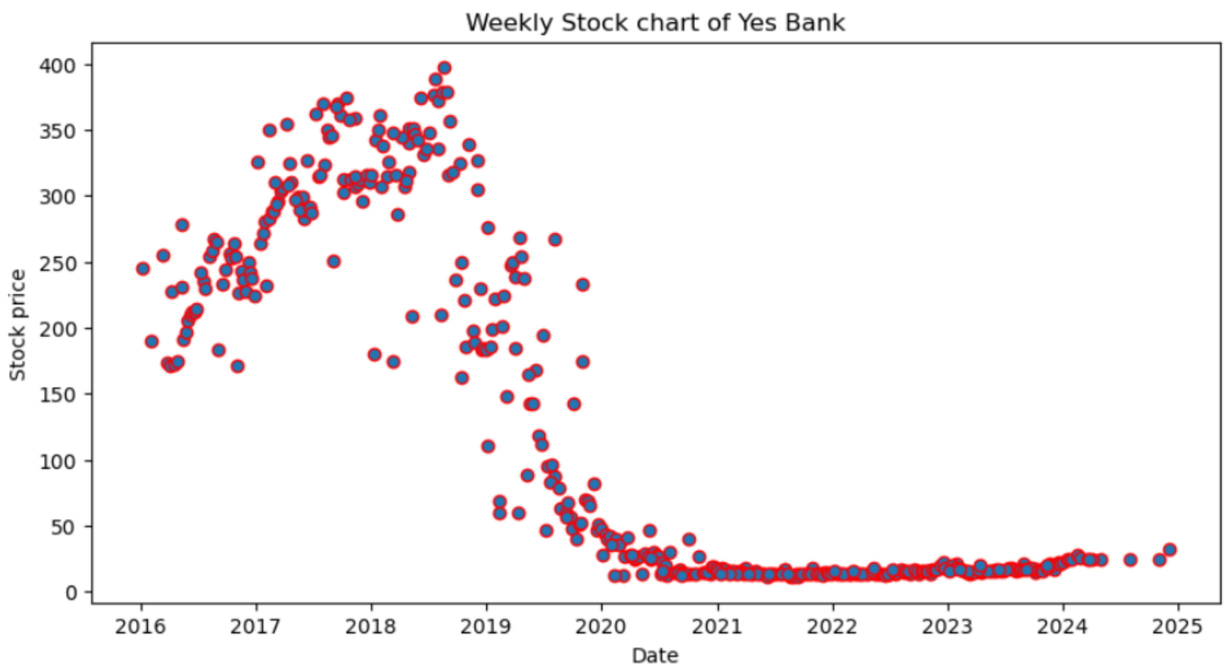

Figure 27: Weekly stock chart of Yes Bank

- From 2016 to 2019, the price surged and reached 400.
- From 2019 to 2020, a strong trend reversal occurred, causing the price to plummet to less than 50.
- From 2020 to the present, the stock price has remained relatively stable and is undergoing consolidation.
- Currently, the stock is not following any clear trend.

Date	ITC_Limited	Bharti_Airtel	Tata_Motors	DLF_Limited	Yes_Bank
2016-03-28	NaN	NaN	NaN	NaN	NaN
2016-04-04	0.004608	-0.044304	0.000000	0.061404	-0.011561
2016-11-04	-0.013761	0.019868	-0.031088	-0.008264	0.000000
2016-04-18	0.037209	0.038961	0.090909	0.016667	0.005848
2016-04-25	-0.040359	-0.003125	0.024510	0.000000	0.017442

Figure 28: Weekly returns of each stock

	Mean Return	Standard Deviation
ITC_Limited	0.002281	0.036127
Bharti_Airtel	0.004029	0.039073
Tata_Motors	0.004088	0.061976
DLF_Limited	0.006540	0.057796
Yes_Bank	-0.000475	0.091095

Figure 29: Mean returns and standard deviation for each stock

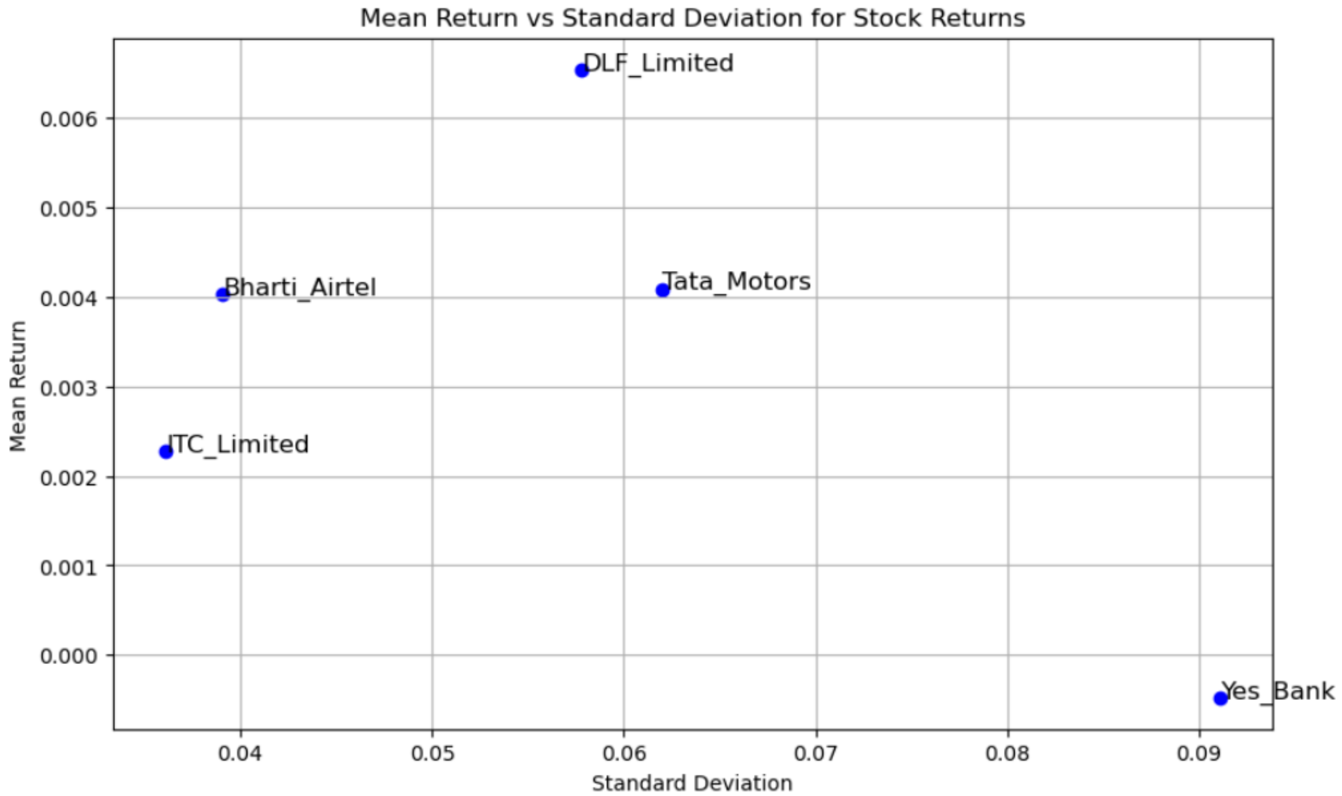

Figure 30: Mean return vs Standard deviation for stock returns

Interpretation of the plot

- ITC_Limited and Bharti_Airtel have relatively low volatility and moderate mean returns.
- Tata_Motors and DLF_Limited have higher volatility compared to ITC_Limited and Bharti_Airtel, but also higher mean returns.
- Yes_Bank has the highest volatility and a negative mean return, indicating it is the riskiest and has been underperforming on average.

Inferences

1. ITC_Limited:

- Mean Return: 0.002281 (0.2281% per week) This means, on average, the stock has increased by 0.2281% each week.
- Standard Deviation: 0.036127 (3.6127% per week) This indicates the volatility of the stock. The weekly returns typically deviate by about 3.6127% from the mean return.

2. Bharti_Airtel:

- Mean Return: 0.004029 (0.4029% per week) On average, the stock has increased by 0.4029% each week.
- Standard Deviation: 0.039073 (3.9073% per week) The weekly returns typically deviate by about 3.9073% from the mean return.

3. Tata_Motors:

- Mean Return: 0.004088 (0.4088% per week) On average, the stock has increased by 0.4088% each week.
- Standard Deviation: 0.061976 (6.1976% per week) The weekly returns typically deviate by about 6.1976% from the mean return, indicating higher volatility compared to ITC Limited and Bharti Airtel.

4. DLF_Limited:

- Mean Return: 0.006540 (0.6540% per week) On average, the stock has increased by 0.6540% each week.
- Standard Deviation: 0.057796 (5.7796% per week) The weekly returns typically deviate by about 5.7796% from the mean return, indicating moderate volatility.

5. Yes_Bank:

- Mean Return: -0.000475 (-0.0475% per week) On average, the stock has decreased by 0.0475% each week.
- Standard Deviation: 0.091095 (9.1095% per week) The weekly returns typically deviate by about 9.1095% from the mean return, indicating the highest volatility among the five stocks.

- ***Mean Return:***

Indicates the average weekly performance of the stock. Positive values suggest that the stock has been increasing on average, while negative values indicate a decline.

- ***Standard Deviation:***

Measures the volatility of the stock returns. Higher values indicate more variability and thus higher risk. Lower values suggest more stable returns.

Insights

1)Low Risk, Moderate Return:

ITC Limited and Bharti Airtel:

- Both stocks have relatively low volatility and offer moderate mean returns.
- These stocks might be suitable for risk-averse investors looking for more stable returns.

2) Moderate to High Risk, High Return Potential:

Tata Motors and DLF Limited:

- These stocks exhibit higher volatility but also offer higher mean returns.
- Suitable for investors willing to take on more risk for the potential of higher returns.

3) High Risk, Negative Return:

Yes Bank:

- This stock has the highest volatility and a negative mean return, indicating poor performance and high risk.
- It may not be a good investment option unless there is a specific strategy to leverage its volatility or there are expectations of a turnaround.

Recommendations

- Diversify investments across stocks with different risk profiles. For example, combining ITC Limited and Bharti Airtel with Tata Motors and DLF Limited could balance the portfolio by mixing stability with high return potential.
- Assess your risk tolerance before investing. If you are risk-averse, prioritize stocks like ITC Limited and Bharti Airtel. If you can tolerate higher risk for potentially higher returns, consider including Tata Motors and DLF Limited.
- Regularly monitor the performance and volatility of the stocks. Rebalance the portfolio as necessary to maintain the desired risk-return profile.
- Be cautious with stocks like Yes Bank. Thoroughly research and understand the reasons behind its negative performance. Consider avoiding or limiting exposure to such high-risk stocks unless there is a compelling reason to invest.

- Stay updated with market trends and news related to these companies. External factors, market conditions, and company-specific news can significantly impact stock performance.
- Consider a long-term investment horizon to ride out short-term volatility, especially for higher-risk stocks. Long-term investments can often yield better returns and mitigate short-term risks.