Finance & Risk Analytics Project

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1.0 PART A: Commercial Credit Risk Analysis

1.1 Definition

1.1.1 Context

In the realm of modern finance, businesses encounter the perpetual challenge of managing debt obligations effectively to maintain a favorable 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.

1.1.2 Objective

Financial Metrics of various companies is given. The objective is to make a Machine Learning model to predict whether a given company will default or not.

1.2 EDA

1.2.1 Basics

1.2.1.1 Shape

The data has 4256 rows and 51 columns.

All columns are of **float64** data type.

1.2.1.2 Data Dictionary

- 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

1.2.1.3 Data Head

	Num	Networth Next Year	Total assets	Net worth	Total income	Change in stock	Total expenses	Profit after tax	PBDITA	PBT	...	Debtors turnover	Finished goods turnover	WIP turnover	Raw material turnover	Shares outstanding	Equity face value
0	1	395.3	827.6	336.5	534.1	13.5	508.7	38.9	124.4	64.6	...	5.65	3.99	3.37	14.87	8760056.0	10.0
1	2	36.2	67.7	24.3	137.9	-3.7	131.0	3.2	5.5	1.0	...	NaN	NaN	NaN	NaN	NaN	NaN
2	3	84.0	238.4	78.9	331.2	-18.1	309.2	3.9	25.8	10.5	...	2.51	17.67	8.76	8.35	NaN	NaN
3	4	2041.4	6883.5	1443.3	8448.5	212.2	8482.4	178.3	418.4	185.1	...	1.91	18.14	18.62	11.11	10000000.0	10.0
4	5	41.8	90.9	47.0	388.6	3.4	392.7	-0.7	7.2	-0.6	...	68.00	45.87	28.67	19.93	107315.0	100.0

1.2.1 - Partial Data Head

1.2.1.4 Descriptive Statistics

	Total_assets	Net_worth	Total_income	Change_in_stock	Total_expenses	Profit_after_tax	PBDITA	PBT	Cash_profit	PBDITA_as_pe
count	4256.0	4256.0	4256.0	4256.0	4256.0	4256.0	4256.0	4256.0	4256.0	
mean	3574.0	1352.0	4688.0	44.0	4356.0	295.0	606.0	410.0	408.0	
std	30074.0	12961.0	52435.0	408.0	50392.0	3024.0	5543.0	4140.0	4068.0	
min	0.0	0.0	0.0	-3029.0	-0.0	-3908.0	-441.0	-3895.0	-2246.0	
25%	91.0	31.0	121.0	-1.0	105.0	1.0	7.0	1.0	3.0	
50%	316.0	105.0	520.0	4.0	471.0	10.0	42.0	14.0	22.0	
75%	1121.0	390.0	1920.0	44.0	1690.0	67.0	192.0	94.0	118.0	
max	1176509.0	613152.0	2442828.0	14186.0	2366035.0	119439.0	208576.0	145293.0	176912.0	

1.2.2 - Descriptive Statistics of partial data

We see that the range of data is very large. There's a big difference between the median and maximum values.

1.2.1.5 Missing Values

```
PE_on_BSE                       61.72
Investments                     40.30
Other_income                    36.56
Contingent_liabilities          32.94
Deferred_tax_liability          32.17
```

1.2.3 - Features with >30% missing values

Features with more than 30% missing data were deleted.
Rest of the values were imputed with Mean because Median value was too small as compared to the range of the data.

1.2.1.6 Creating 'default' feature

0 = Non defaulter = Networth Next Year > 0

1 = Defaulter = Networth Next Year < 0

Value Counts of feature:

0 : 3352 nos. = 78.75%

1 : 904 nos. = 25.25%

1.2.1.7 Outlier Removal

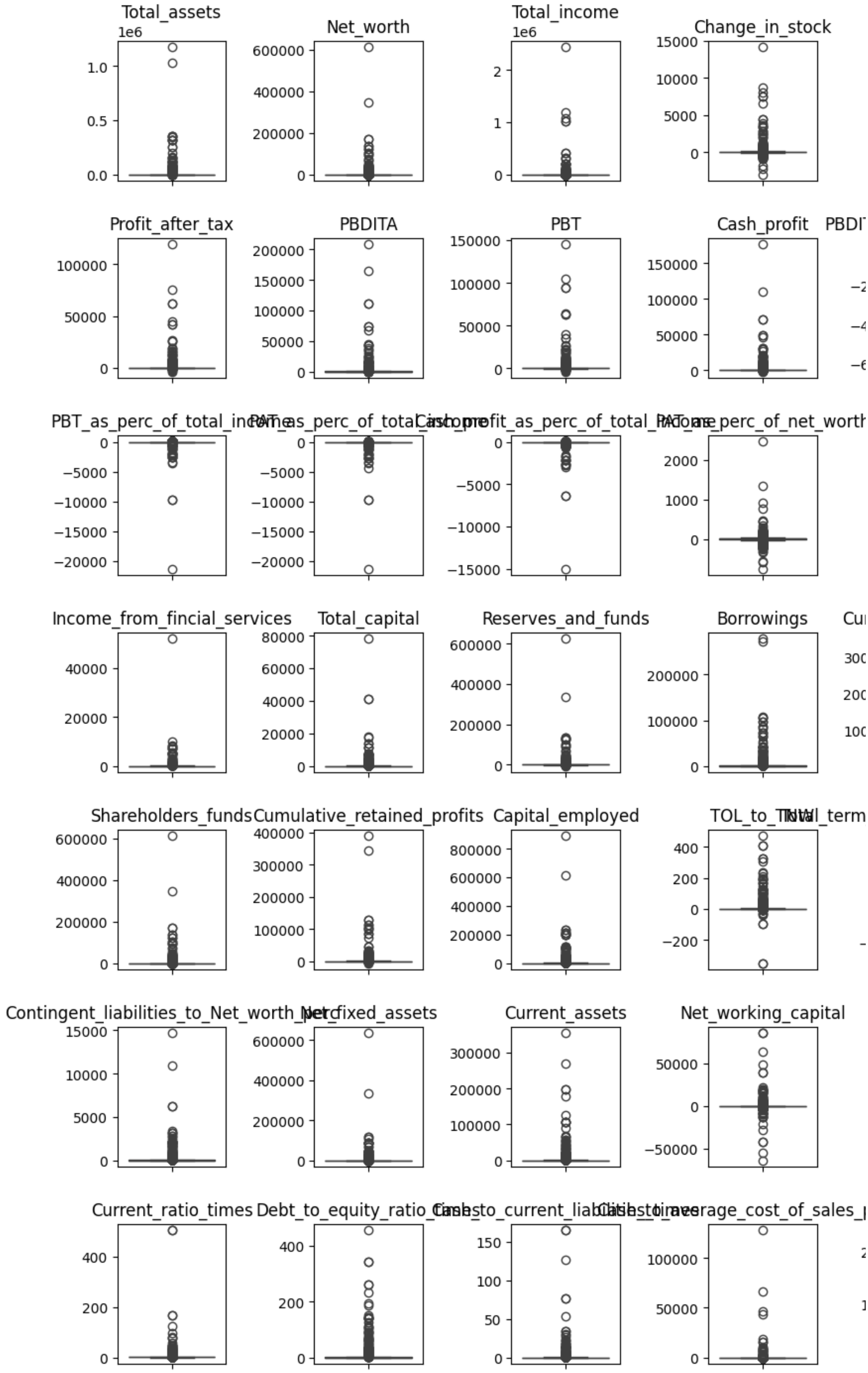
Equity_face_value	31.56
Adjusted_EPS	6.02
Net_working_capital	5.19
EPS	4.96
Cumulative_retained_profits	4.49
Profit_after_tax	4.42
PBT	4.09
Total_assets	4.06
Total_liabilities	4.06

1.2.4 - Features with most outliers in percentage terms

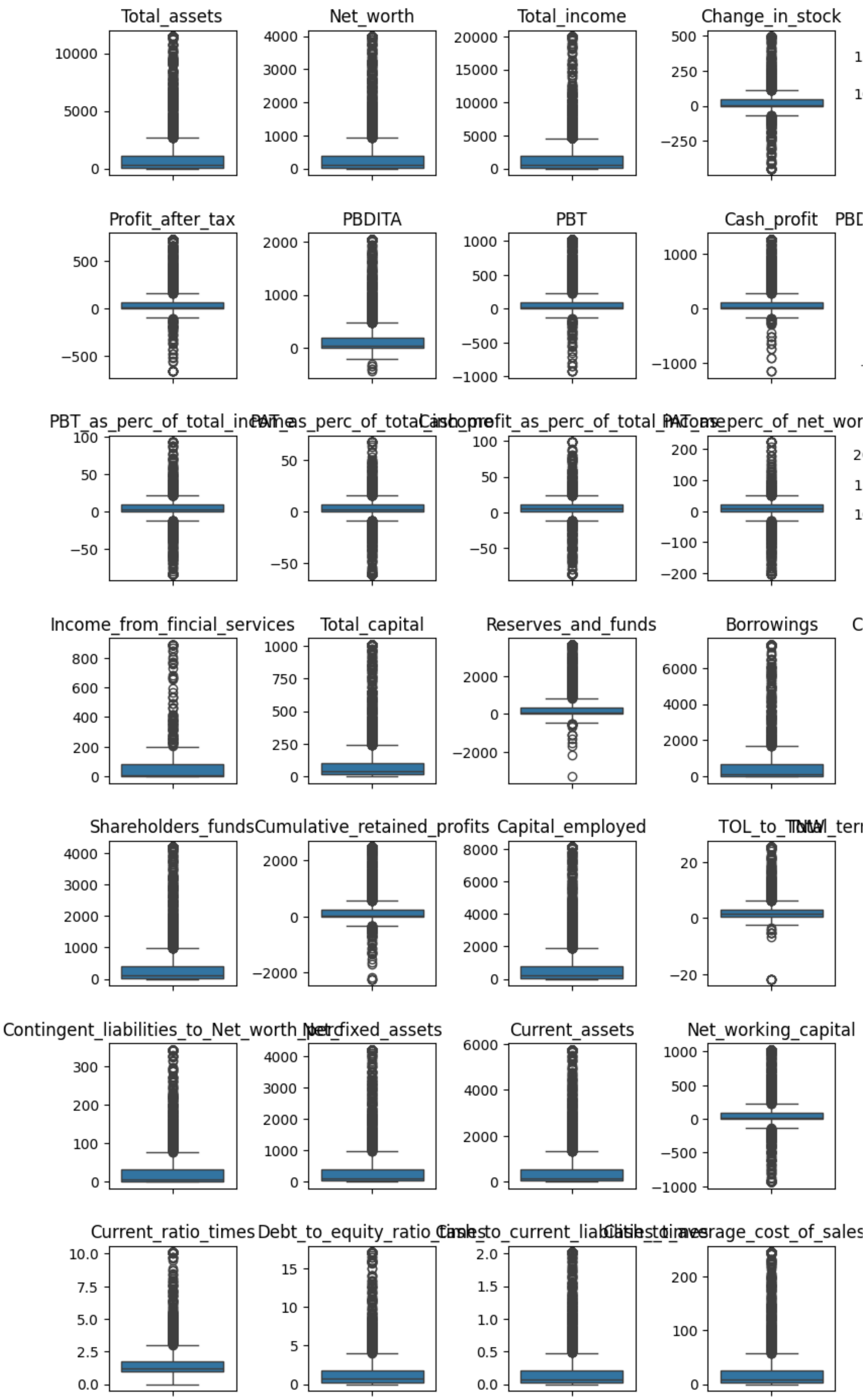
Outliers were removed using ± 10 x IQR for lower and upper ranges, since the range of values is very large in each feature of the data.

1.2.2 Univariate Analysis

1.2.2.1 Before and After Outlier Removal

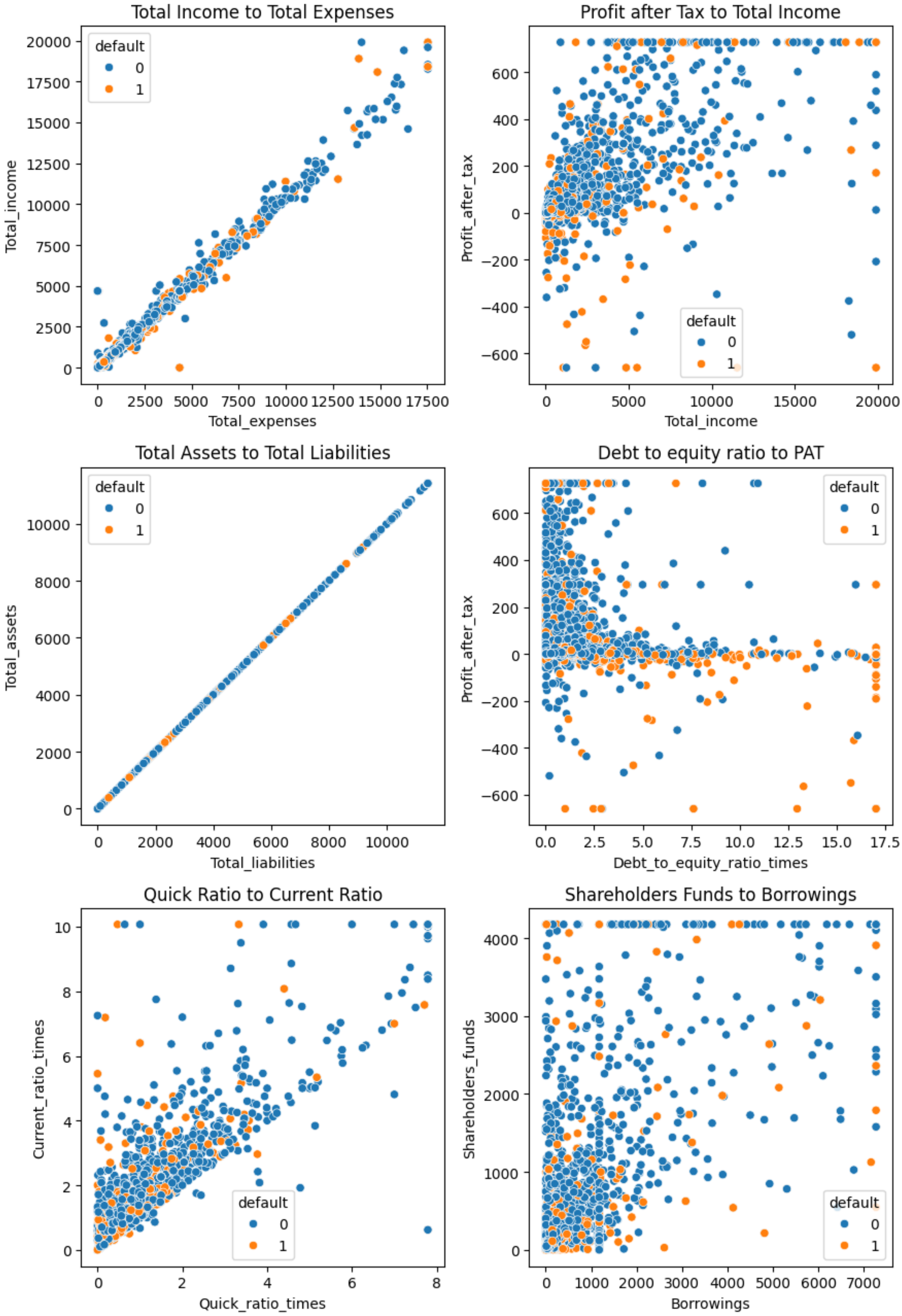


1.2.5 - Boxplots of selected features before Outlier Removal

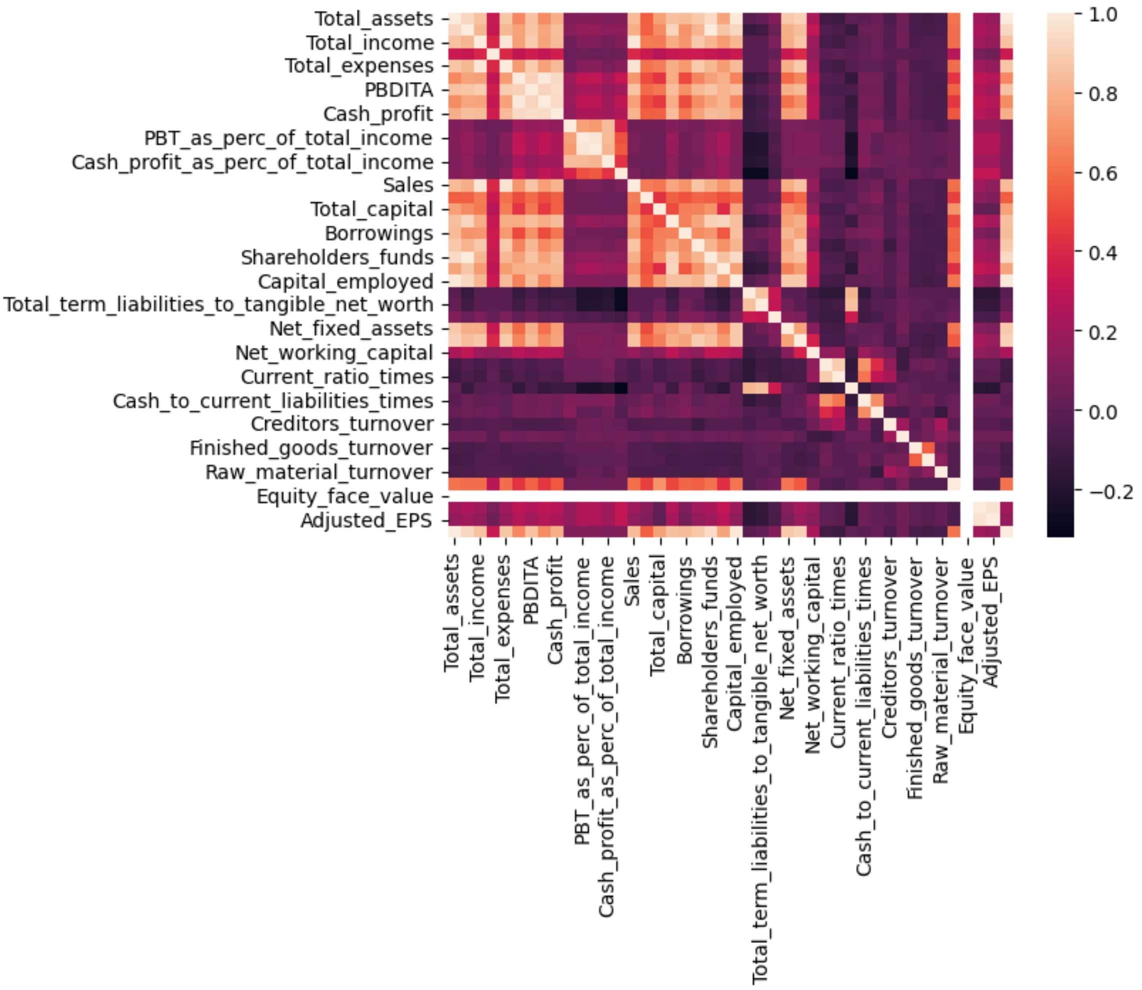


1.2.6 - Boxplots of selected features after Outlier Removal

1.2.3 Multivariate Analysis



1.2.7 - Scatterplots of key variables differentiated by defaulters



1.2.8 - Correlation heatmap of partial data

1.2.4 Observations

- There is quite some multicollinearity present in the data.
- Total income and total expenses are highly correlated and there is no imbalance in the distribution between defaulters and non defaulters.
- Defaulters are concentrated in the Low PAT to Low Total Income region.
- Total Assets and Total Liabilities are highly correlated for all levels
- Defaulters are concentrated in the 0 PAT region with all levels of Debt to Equity Ratio.
- Most companies are concentrated in the low Shareholder Funds to Borrowings region, and so are the defaulters.

1.3 Model Building

1.3.1 Metrics of Choice

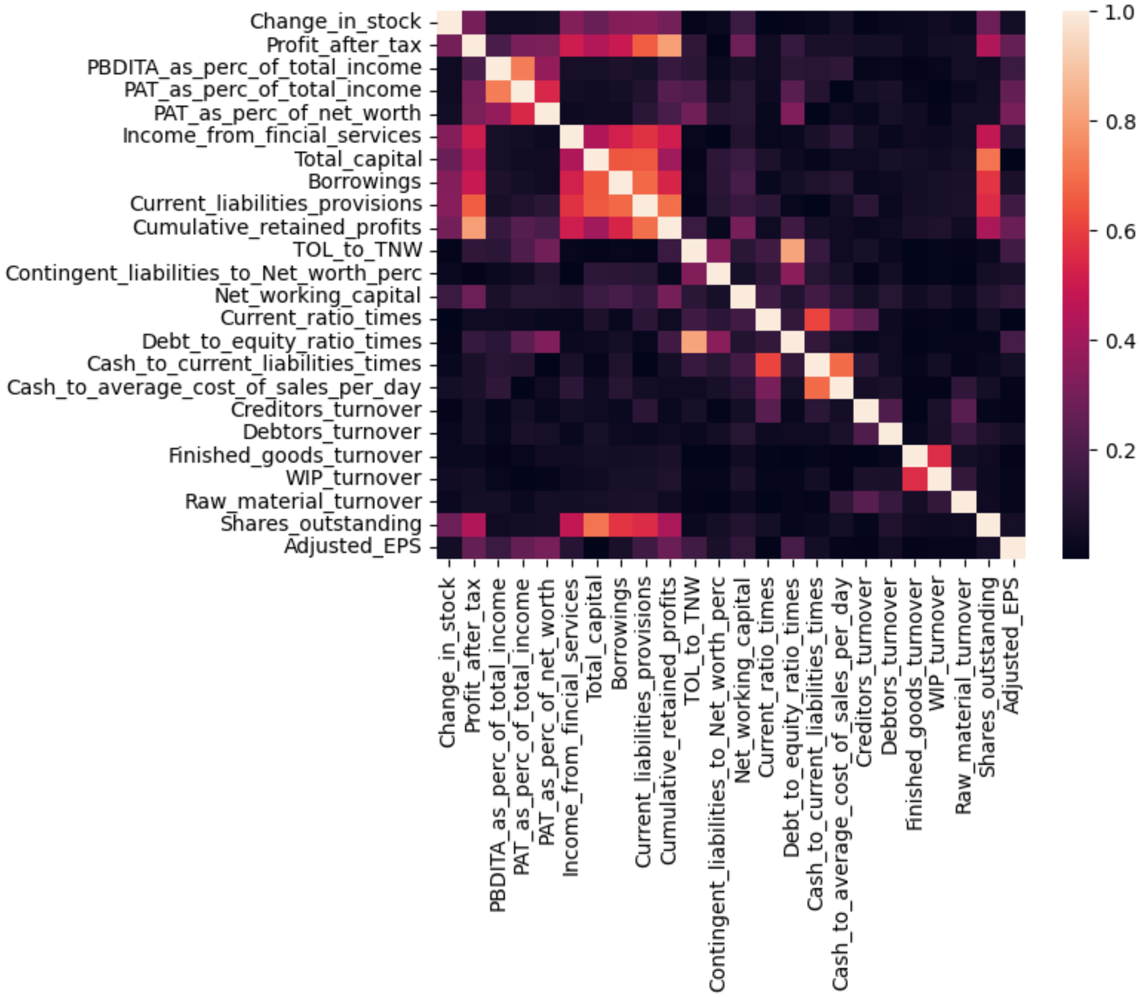
1. **Recall for Defaulters** = Low False Negatives : If this metric is high, more Defaulters will be correctly identified and Loans given to them would decrease. This is important because this would Minimize the Bank's Losses.
2. **Precision for Defaulters** = Low False Positives : If this metric is high, more non-Defaulters will be correctly identified and more Loans will be given to them. This is important because this would Maximize the Bank's Revenue.

Therefore both these metrics will be important for us.

1.3.2 Multicollinearity Elimination using VIF and Correlation

	variables	VIF
0	Current_liabilities_provisions	4.533108
1	Cumulative_retained_profits	4.449202
2	Debt_to_equity_ratio_times	4.370025
3	TOL_to_TNW	4.238168
4	Profit_after_tax	4.158309
5	Cash_to_current_liabilities_times	3.910097
6	Total_capital	3.677287
7	Borrowings	2.998626
8	Current_ratio_times	2.987144
9	Shares_outstanding	2.897508
10	PBDITA_as_perc_of_total_income	2.781516
11	PAT_as_perc_of_total_income	2.766942
12	Cash_to_average_cost_of_sales_per_day	2.765938
13	WIP_turnover	2.125895
14	Income_from_fincial_services	2.089950
15	Finished_goods_turnover	1.873372
16	PAT_as_perc_of_net_worth	1.743382
17	Creditors_turnover	1.692928
18	Raw_material_turnover	1.545379
19	Debtors_turnover	1.526982
20	Contingent_liabilities_to_Net_worth_perc	1.446836
21	Adjusted_EPS	1.382045
22	Net_working_capital	1.317634
23	Change_in_stock	1.278211

1.3.1 - Remaining columns after removal of features with high VIF



1.3.2 - Correlation heatmap of remaining features

	Feature 1	Feature 2	Correlation
2	TOL_to_TNW	Debt_to_equity_ratio_times	0.82
3	Debt_to_equity_ratio_times	TOL_to_TNW	0.82
0	Profit_after_tax	Cumulative_retained_profits	0.80
1	Cumulative_retained_profits	Profit_after_tax	0.80

1.3.3 - Feature pairs with correlation > 0.8

Features 'TOL_to_TNW' and 'Cumulative_retained_profits' were removed.

1.3.3 Model 1 - Logistic Regression

Dep. Variable:	default	**No. Observations:**	2979
Model:	Logit	**Df Residuals:**	2956
Method:	MLE	**Df Model:**	22
Date:	Tue, 10 Sep 2024	**Pseudo R-squ.:**	0.05189
Time:	12:37:45	**Log-Likelihood:**	-1460.9
converged:	True	**LL-Null:**	-1540.8
Covariance Type:	nonrobust	**LLR p-value:**	6.323e-23

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-1.5384	0.109	-14.100	0.000	-1.752	-1.325
Change_in_stock	0.0002	0.001	0.274	0.784	-0.001	0.001
Profit_after_tax	0.0004	0.000	1.060	0.289	-0.000	0.001
PBDITA_as_perc_of_total_income	-0.0011	0.003	-0.332	0.740	-0.008	0.005
PAT_as_perc_of_total_income	-0.0048	0.005	-1.044	0.297	-0.014	0.004
PAT_as_perc_of_net_worth	-0.0069	0.002	-4.005	0.000	-0.010	-0.004
Income_from_fincial_services	-6.302e-05	0.001	-0.112	0.911	-0.001	0.001
Total_capital	0.0005	0.000	1.361	0.174	-0.000	0.001
Borrowings	-3.438e-05	5.45e-05	-0.630	0.528	-0.000	7.25e-05
Current_liabilities_provisions	-3.108e-05	0.000	-0.261	0.794	-0.000	0.000
Contingent_liabilities_to_Net_worth_perc	1.697e-06	0.001	0.002	0.998	-0.001	0.001
Net_working_capital	7.534e-06	0.000	0.041	0.967	-0.000	0.000
Current_ratio_times	-0.0599	0.041	-1.479	0.139	-0.139	0.020
Debt_to_equity_ratio_times	0.1055	0.015	6.845	0.000	0.075	0.136
~~Cash_to_current_liabilities_times~~	~~0.0496~~	~~0.167~~	~~0.265~~	~~0.791~~	~~-0.316~~	~~0.416~~
Cash_to_average_cost_of_sales_per_day	0.0021	0.001	1.947	0.051	-1.38e-05	0.004
Creditors_turnover	0.0063	0.002	2.720	0.007	0.002	0.011
Debtors_turnover	-0.0015	0.002	-0.602	0.547	-0.006	0.003
Finished_goods_turnover	0.0003	0.001	0.486	0.627	-0.001	0.001
WIP_turnover	-0.0002	0.002	-0.134	0.893	-0.004	0.003
Raw_material_turnover	0.0001	0.003	0.037	0.971	-0.006	0.006
Shares_outstanding	-2.041e-09	2e-09	-1.023	0.306	-5.95e-09	1.87e-09
Adjusted_EPS	-0.0003	0.002	-0.153	0.878	-0.005	0.004

1.3.4 - Results of first model

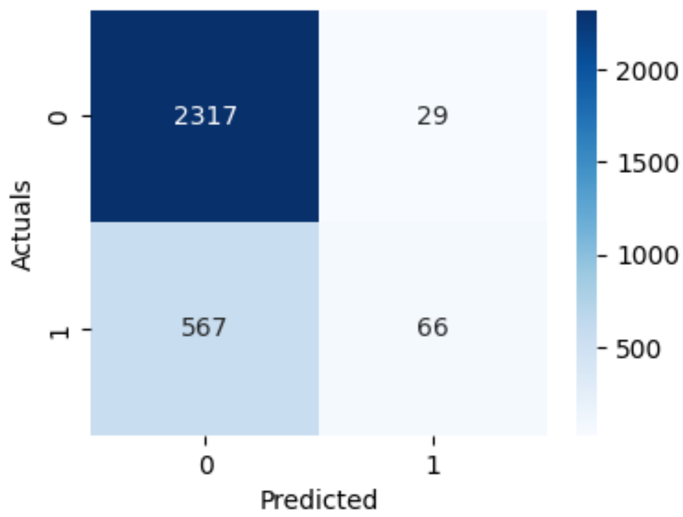
Features with higher P values were removed one by one until P value of no feature was greater than 0.05. It resulted in the following model:

Dep. Variable:	default	**No. Observations:**	2979
Model:	Logit	**Df Residuals:**	2973
Method:	MLE	**Df Model:**	5
Date:	Tue, 10 Sep 2024	**Pseudo R-squ.:**	0.04959
Time:	12:38:00	**Log-Likelihood:**	-1464.4
converged:	True	**LL-Null:**	-1540.8
Covariance Type:	nonrobust	**LLR p-value:**	3.365e-31

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Intercept	-1.6013	0.070	-22.771	0.000	-1.739	-1.463
PAT_as_perc_of_total_income	-0.0055	0.003	-1.643	0.100	-0.012	0.001
PAT_as_perc_of_net_worth	-0.0064	0.002	-3.920	0.000	-0.010	-0.003
Debt_to_equity_ratio_times	0.1065	0.014	7.580	0.000	0.079	0.134
Cash_to_average_cost_of_sales_per_day	0.0018	0.001	2.455	0.014	0.000	0.003
Creditors_turnover	0.0049	0.002	2.315	0.021	0.001	0.009

1.3.5 - Logistic Regression model after refinement

1.3.3.1 Predictions on Model 1 Train Data



1.3.6 - Confusion matrix of train data

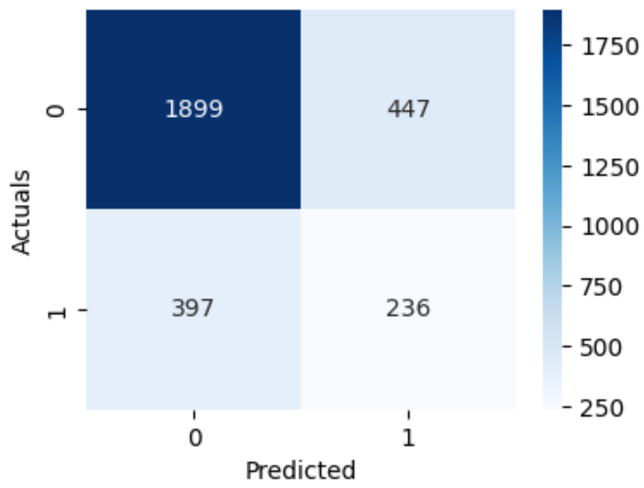
	precision	recall	f1-score	support
0	0.80	0.99	0.89	2346
1	0.69	0.10	0.18	633
accuracy			0.80	2979
macro avg	0.75	0.55	0.53	2979
weighted avg	0.78	0.80	0.74	2979

1.3.7 - Classification report on train data

1.3.3.2 Predictions using Optimal Threshold

The Optimal Threshold was found to be 0.234

Train Data:

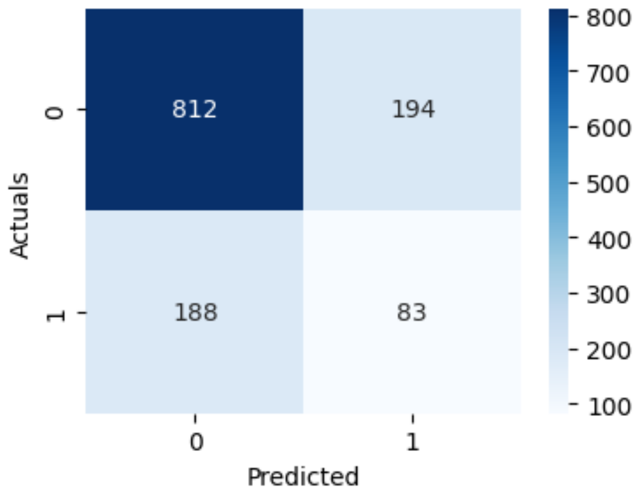


1.3.8 - Confusion matrix on train data

	precision	recall	f1-score	support
0	0.83	0.81	0.82	2346
1	0.35	0.37	0.36	633
accuracy			0.72	2979
macro avg	0.59	0.59	0.59	2979
weighted avg	0.72	0.72	0.72	2979

1.3.9 - Classification report on train data

Test Data:

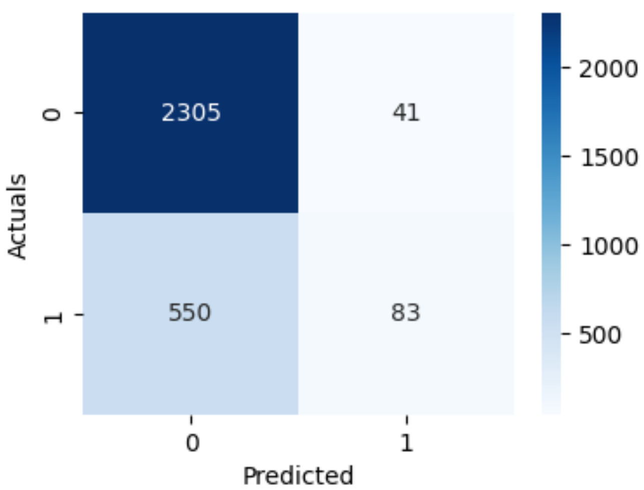


1.3.10 - Confusion matrix of test data

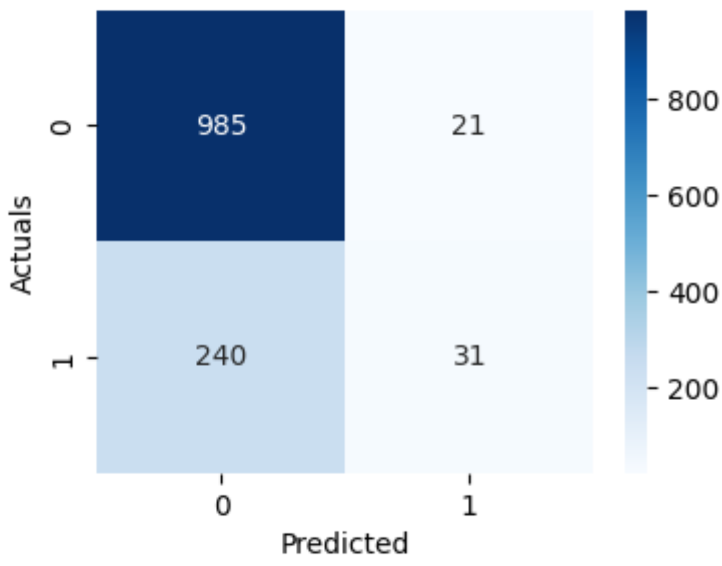
	precision	recall	f1-score	support
0	0.81	0.81	0.81	1006
1	0.30	0.31	0.30	271
accuracy			0.70	1277
macro avg	0.56	0.56	0.56	1277
weighted avg	0.70	0.70	0.70	1277

1.3.11 - Classification report on test data

1.3.4 Model 2 - Linear Discriminant Analysis



1.3.12 - LDA confusion matrix on train data



1.3.13 - LDA Confusion matrix on Test data

	precision	recall	f1-score	support
0	0.81	0.98	0.89	2346
1	0.67	0.13	0.22	633
accuracy			0.80	2979
macro avg	0.74	0.56	0.55	2979
weighted avg	0.78	0.80	0.74	2979

1.3.14 - LDA Classification resport on Train data

	precision	recall	f1-score	support
0	0.80	0.98	0.88	1006
1	0.60	0.11	0.19	271
accuracy			0.80	1277
macro avg	0.70	0.55	0.54	1277
weighted avg	0.76	0.80	0.74	1277

1.3.15 - LDA Classification report on Test data

1.3.5 Model 3 - Random Forest

1.3.5.1 Hyperparameter Tuning

Parameter options:

'max_depth': [3,5,7,9],

'min_samples_leaf': [5, 10, 15, 20],

'min_samples_split': [15, 30, 45, 60],

'n_estimators': [25, 50, 75]

Best Parameters:

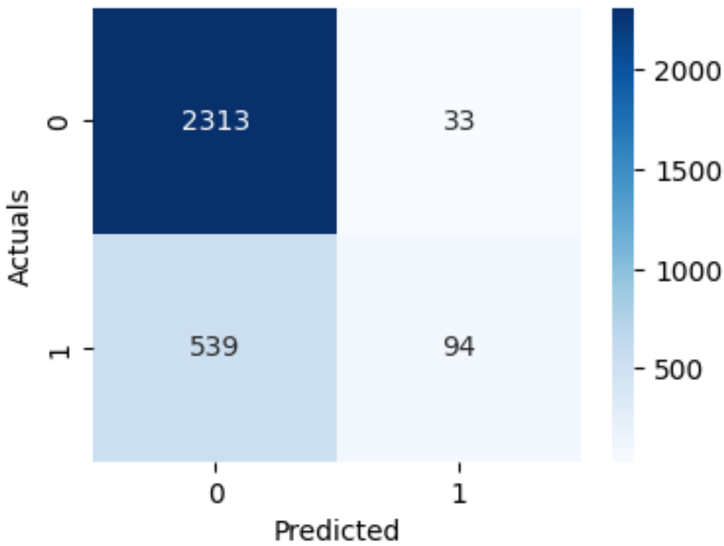
'max_depth': 7,

'min_samples_leaf': 15,

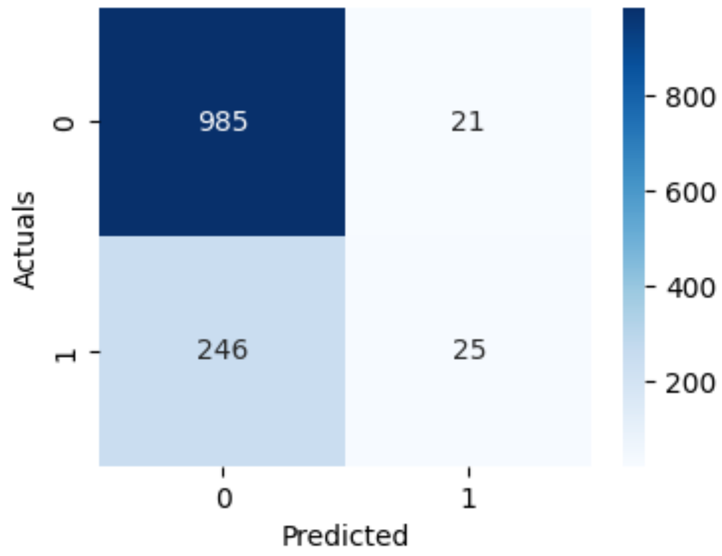
'min_samples_split': 15,

'n_estimators': 50

1.3.5.2 Predictions using Best Parameters



1.3.16 - RF Confusion matrix on Train data



1.3.17 - RF Confusion matrix on Test data

	precision	recall	f1-score	support
0	0.81	0.99	0.89	2346
1	0.74	0.15	0.25	633
accuracy			0.81	2979
macro avg	0.78	0.57	0.57	2979
weighted avg	0.80	0.81	0.75	2979

1.3.18 - RF Classification report on Train data

	precision	recall	f1-score	support
0	0.80	0.98	0.88	1006
1	0.54	0.09	0.16	271
accuracy			0.79	1277
macro avg	0.67	0.54	0.52	1277
weighted avg	0.75	0.79	0.73	1277

1.3.19 - RF Classification report on Test data

1.3.6 Model Performance Comparison

Model	Precision for 1	Recall for 1	Recall for 0	Precision for 0
Logistic Regression	0.30	0.31	0.81	0.83
Linear Discriminant	0.60	0.11	0.98	0.80
Random Forest	0.54	0.09	0.98	0.80

1. Logistic Regression - Balanced Precision and Recall for Defaulters but still not better than random selection.
2. Linear Discriminant - High Precision and Recall for non-Defaulters with abysmal Recall for Defaulters and average Precision for Defaulters.
3. Random Forest - Similar to Linear Discriminant but slightly less Precision and Recall for Defaulters.

1.3.6.1 Final Model Selection

Final model selected can be either **Linear Discriminant or Random Forest**.

Reasoning:

1. **Med-High Precision for Non-Defaulters** - This metric ensures that when the model predicts a Non-Defaulter, we can be 80% sure that it will be a non-Defaulter, and therefore the Bank can confidently give out a loan.
2. Precision for Defaulters is similar and average - Precision for Defaulters is only 60% that means when the model predicts a Defaulter, only 60% will turn out to be Defaulters.
3. Recall for Defaulters is similar and bad - 11% Recall is much less than Random Selection and is therefore useles. This means the model is missing ~90% of Defaulters.

1.3.6.2 Important Features

Feature	Importance
Debt_to_equity_ratio_times	0.145
Current_ratio_times	0.059
Cash_to_current_liabilities_times	0.048
PAT_as_perc_of_net_worth	0.008
Creditors_turnover	0.007

1.3.20 - Top 5 features for LDA model

Feature	Importance
Debt_to_equity_ratio_times	0.177
PAT_as_perc_of_net_worth	0.148
Profit_after_tax	0.075
Adjusted_EPS	0.062
PAT_as_perc_of_total_income	0.061

1.3.21 - Top 5 features of Random Forest model

‘Debt to Equity ratio’ and ‘PAT as % of Net Worth’ are common to both models.

1.3.7 Actionable Insights and Recommendations

- Pay attention to ‘Debt to Equity ratio’ and ‘PAT as % of Net Worth’.
    - More the D/E ratio, more the chances of default.
    - More PAT as % of Net Worth less the chances of default.
    - Other important features are given in the tables above.

- When the model predicts a Non-Defaulter, because of Precision of Class 0 you can be 80% sure it would be a Non-Defaulter and give out loans accordingly.
- Low Recall (11%) of Defaulters tells us that the model is not catching Defaulters
- But when the model does predict a Defaulter, because of Precision of Defaulters, we can be 60% sure that it's a defaulter.

2.0 Part B : Market Risk Analysis

2.1 Plots

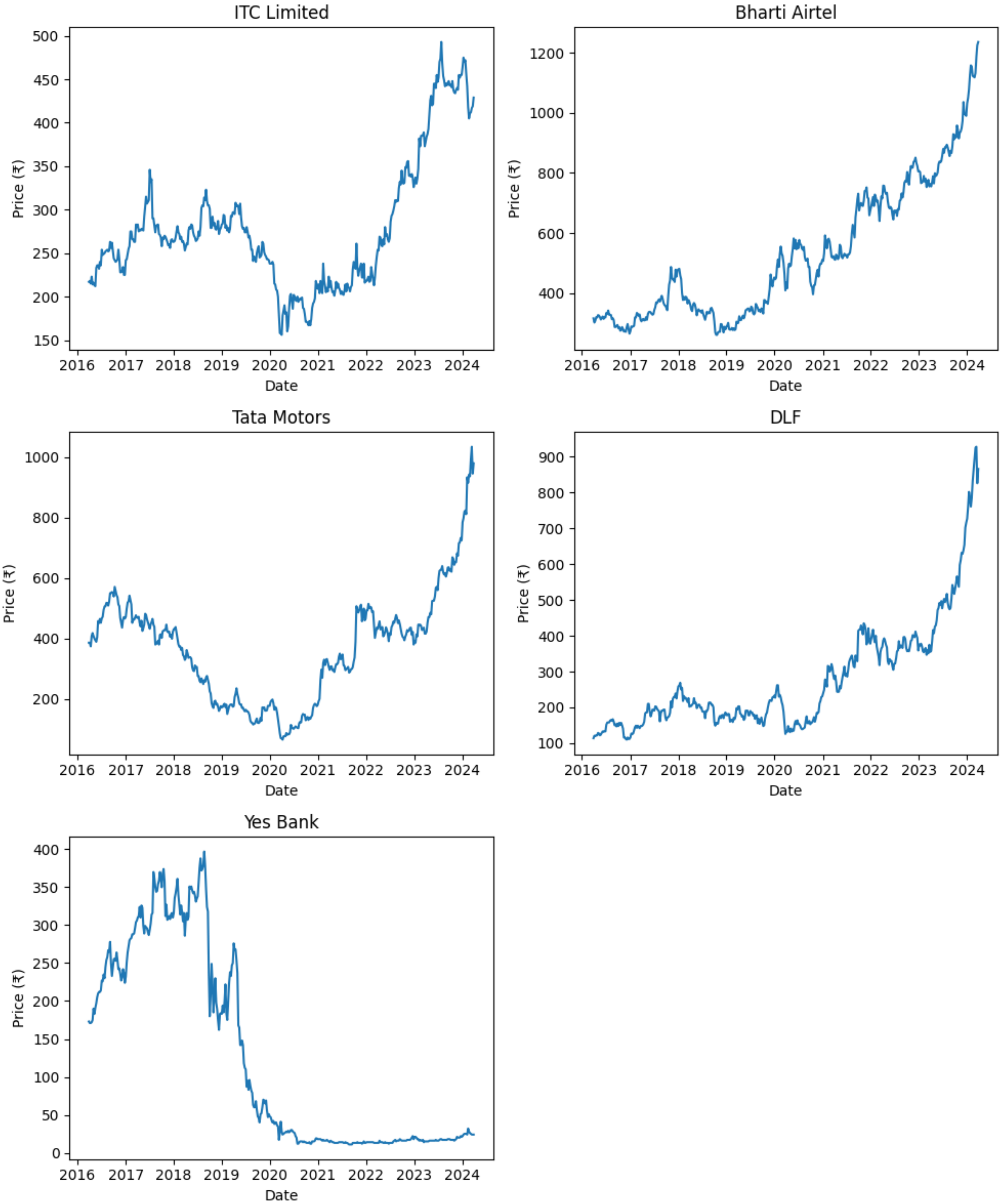
	Date	ITC Limited	Bharti Airtel	Tata Motors	DLF Limited	Yes Bank
0	28-03-2016	217	316	386	114	173
1	04-04-2016	218	302	386	121	171
2	11-04-2016	215	308	374	120	171
3	18-04-2016	223	320	408	122	172
4	25-04-2016	214	319	418	122	175

2.1.1 - Data head

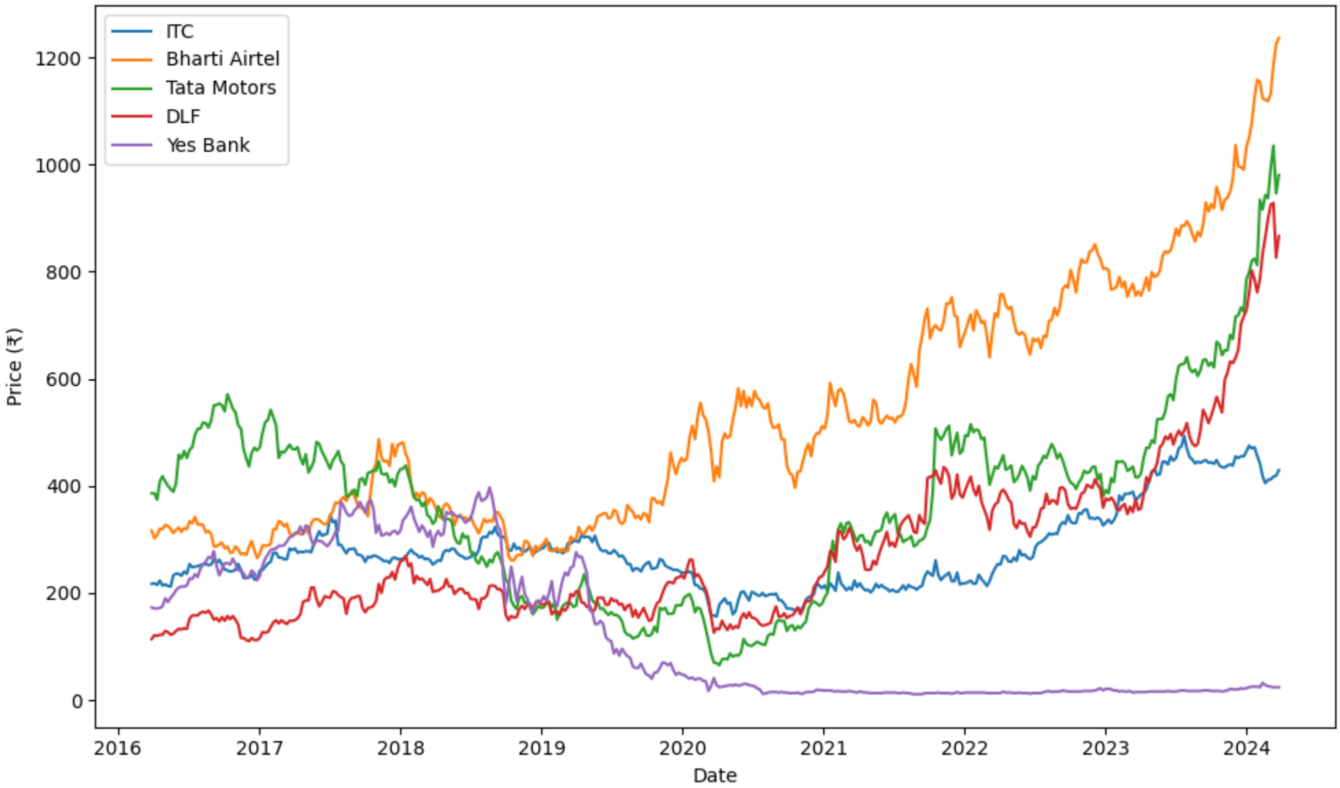
The data consists of 418 rows and 6 columns, including a Date column. The stock prices are given on a Weekly basis.

	ITC Limited	Bharti Airtel	Tata Motors	DLF Limited	Yes Bank
count	418.0	418.0	418.0	418.0	418.0
mean	279.0	528.0	369.0	277.0	124.0
std	75.0	227.0	182.0	156.0	130.0
min	156.0	261.0	65.0	110.0	11.0
25%	224.0	334.0	186.0	166.0	16.0
50%	266.0	478.0	400.0	213.0	30.0
75%	304.0	707.0	466.0	360.0	250.0
max	493.0	1236.0	1035.0	928.0	397.0

2.1.2 - Descriptive statistics of the data



2.1.3 - Plots of all stocks



2.1.4 - Plot of all stocks together

2.1.1 Observations

- 2020 onwards all 3 stocks have a major upward trend - Bharti Airtel, Tata Motors, and DLF.

2.2 Returns Calculation & Analysis

2.2.1 Process

1. Log was taken of entire data taken and differencing was done to give returns for each period.
2. Mean of these returns is the Average return of the stock per time period.
3. Standard Deviation of these returns is the Volatility of the stock per time period.
4. Sensex values were added from the same period.
5. All values were converted to percentage terms.
6. Points were plotted.

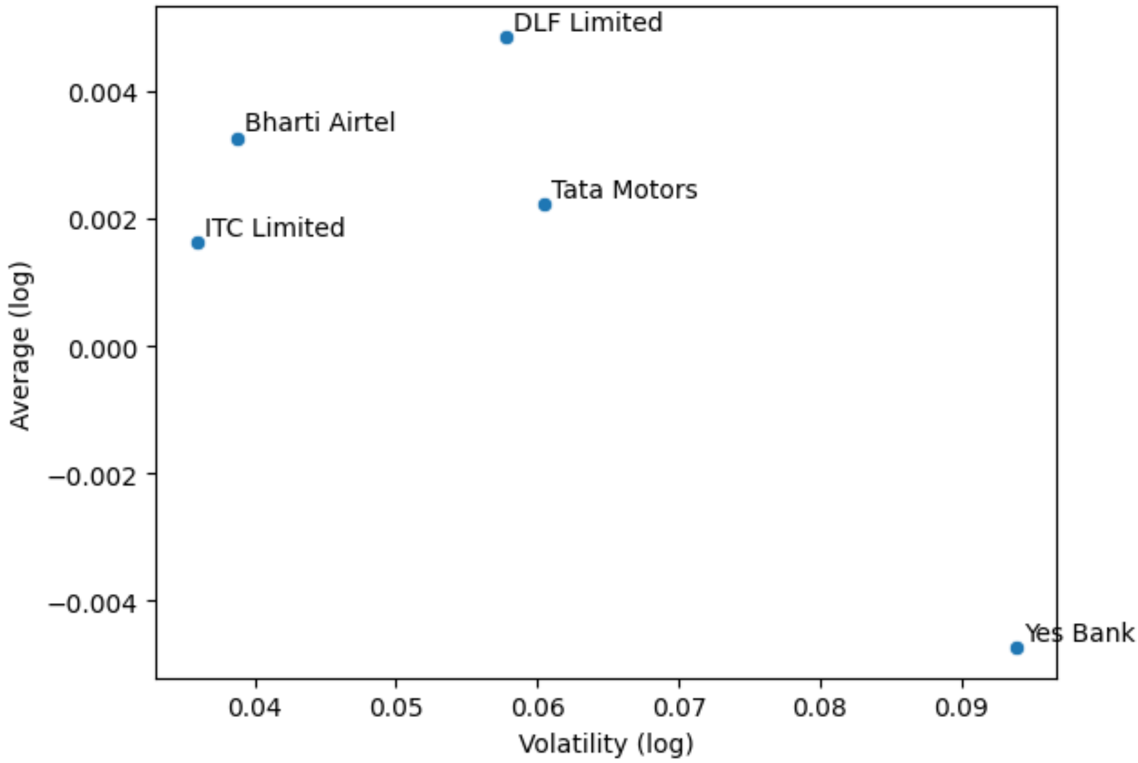
2.2.2 Taking Log and plotting Log values

	ITC Limited	Bharti Airtel	Tata Motors	DLF Limited	Yes Bank
0	NaN	NaN	NaN	NaN	NaN
1	0.004598	-0.045315	0.000000	0.059592	-0.011628
2	-0.013857	0.019673	-0.031582	-0.008299	0.000000
3	0.036534	0.038221	0.087011	0.016529	0.005831
4	-0.041196	-0.003130	0.024214	0.000000	0.017291

2.2.1 - Data after taking Log and differencing

	Average (log)	Volatility (log)
ITC Limited	0.001634	0.035904
Bharti Airtel	0.003271	0.038728
Tata Motors	0.002234	0.060484
DLF Limited	0.004863	0.057785
Yes Bank	-0.004737	0.093879

2.2.2 - Average and Volatility of stocks



2.2.3 - Plot of Log values

2.2.3 Adding Sensex values

	Date	Price	Open	High	Low	Vol.	Change %
0	05-09-2024	82,191.84	82,469.79	82,565.44	82,158.74	5.82M	-0.20%
1	04-09-2024	82,352.64	81,845.50	82,408.54	81,833.69	9.05M	-0.25%
2	03-09-2024	82,555.44	82,652.69	82,675.06	82,400.76	4.32M	-0.01%
3	02-09-2024	82,559.84	82,725.28	82,725.28	82,440.93	9.50M	0.24%
4	30-08-2024	82,365.77	82,637.03	82,637.03	82,256.02	10.31M	0.28%

2.2.4 - Sensex data head

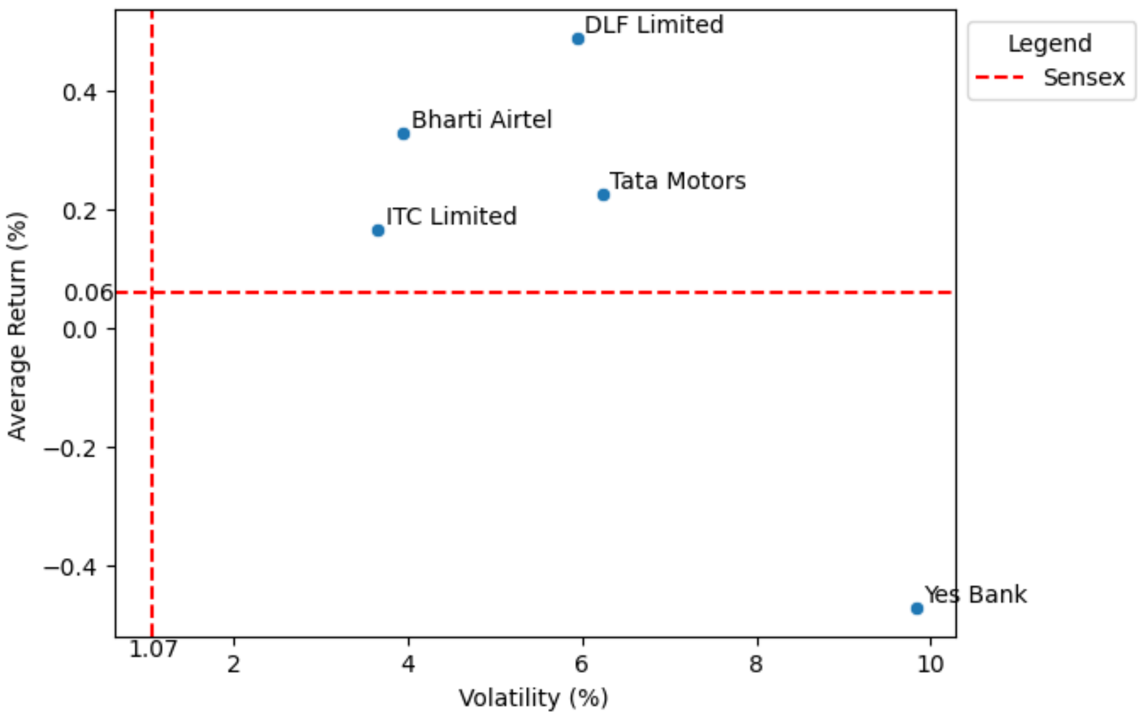
'Change %' column gives us the necessary data.

The Average Return for Sensex is 0.059% and Volatility is 1.065%

2.2.4 Converting to Percentage and Plotting

	Average (%)	Volatility (%)
ITC Limited	0.163577	3.655608
Bharti Airtel	0.327608	3.948763
Tata Motors	0.223683	6.235108
DLF Limited	0.487440	5.948690
Yes Bank	-0.472558	9.842660

2.2.5 - Return and Volatility values in percentage terms



2.2.6 - Plot of all stocks compared to Sensex in percentages

2.3 Actionable Insights & Recommendations

- All stocks give returns higher than Sensex except Yes Bank.
- ITC and Bharti Airtel have similar risk but Bharti Airtel has twice the returns. Those with lower risk appetite should keep these stocks in their portfolio.
- DLF and Tata Motors are considerably more risky than ITC and Bharti Airtel. Those with higher risk appetite should keep these stocks in their portfolio.
- DLF and Tata Motors are similar in risk but DLF has given much more returns.
- Yes Bank has been the riskiest stock and has also given the least returns. But it's now available at a very good price therefore if there is a strong reason to buy the stock according to financial analysis then this is the time to buy.
- Overall this is a well balanced portfolio with most stocks outperforming the index but then the risk is also more than the index. Therefore the investor needs to be careful.