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Evaluation of Credit Risk in Indian Banks: A Comparative Approach Using Panel Data Regression and Random Forest

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ABSTRACT

Purpose: This study evaluates the comparison of classical econometric panel data regression and robust machine learning techniques in the prediction of credit risk across selected banks in India.
Methodology: The research analyses the panel data from 2020-21 to 2024-25. The traditional fixed-effects regression model was validated against ML classifiers such as Random Forest and Decision Trees. To assess predictive accuracy in credit risk management.
Findings: The outcome of the study exhibits that an increase in NPA will cause a credit risk in the banking sector. While the financial indicators, such as Return on Assets (ROA) and Capital Adequacy Ratio (CAR), help to eliminate NPAs. Among these models tested were the Random Forest and the decision tree, which provide valuable insights for Banking and financial institutions, Risk Managers, Regulators, and Policy makers in terms of valuing AI tools to enhance financial oversight for decision-making in the banks.
Originality: This research fills a critical gap in the literature by examining benchmark performance in predicting non-linear machine learning ensembles against econometric tools within the robust supervisory regulatory framework in the banking sector
Practical Implication: Banking and financial institutions can significantly enhance predictive accuracy in the detection of fraud and default in risk management by taking proactive measures to mitigate NPAs. Besides, integrating AI & ML can provide early detection warning, and it facilitates a shift towards reactive to proactive risk management practices in the banks.

Keywords: *Credit Risk, Panel Data Regression, Decision Tree and Random Forest.*

1. INTRODUCTION

The Banking and financial institution system plays a significant role in enhancing the economic well-being of the country by mediating the role between borrowers and savers. They deploy idle public savings and channelise them into productive investments such as Infrastructure development, entrepreneurship, Employment growth, and overall economic resilience. Credit risk Management is a pivotal component of maintaining financial soundness in the banking sector. During the pandemic period, there was a rise in the level of Non-Performing Assets (NPAs). Thus, there is a prerequisite for advanced and effective methods for forecasting the credit risk. Credit risk management involves identifying, assessing, monitoring, and minimizing risk if the borrower defaults on the debts and the lender will increase the risk by aligning expected returns. Credit is a contractual obligation where the borrower gets a loan and ensures remittance of payment at a later time**. (Oyetola *et al.,* 2023).** The significance of credit risk in India was emphasized by past stress-testing analysis conducted on Scheduled Commercial Banks. According to the estimation, it denotes that under a severe stress shock scenario, it has defined two standard deviation increases in Gross Non-Performing Assets (GNPA). The overall GNPA ratio of 46 selected banks could rise from 2.3% to 7.9%. Such changes would substantially damage the capital structure, capital reduction to the Risk-

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weighted Assets Ratio by 370 basis points. Although the overall banking industry is anticipated to remain above the prescribed regulatory requirements of the threshold limits. The traditional models of sensitivity struggle with individual bank failure and due to credit risk. Thus, there is a requirement for advanced AI models to focus on non-linear relationships, identifying complex patterns, changes happens in credit risk, and for leveraging across extensive data among banks and companies. **(RBI Financial Stability Report, 2024).** Credit risk modelling aids banks and other financial institutions in making informed lending decisions, optimising portfolios, and diversifying risk. If the banks and the financial institutions fail to manage the credit risk, it can lead to bankruptcy, financial crisis and increased Non-performing Assets. The traditional credit risk modelling is the traditional method used by banks or financial institutions for evaluating borrower default risk, and the method includes: logistic regression, panel data regression analysis and Probabilistic Graphical Methods, which is a robust framework enhancing credit risk management. This represents dependencies between random variables that predict a clear understanding of credit risk. Thus, this study highlights that the traditional models provide less accuracy and interpretability than PGM (**Oye *et al.,* 2025).** The transformation of AI-driven technologies has restructured the prediction of credit risk and fraud detection. However, in the rapid growth of AI-driven technologies, AI should ensure necessary transparency, cybersecurity, privacy risks, regulatory risks, data biases and lack of interpretation. **Gates, Noah, and Will Flynn. (2025).**

2. LITERATURE REVIEW

The Credit risk models were used to evaluate the probability of a borrower's default, financial crisis of the bank or financial institutions. The models can be classified into traditional-based models and Artificial Intelligence (AI) – Machine Learning Technique models. The traditional credit risk management models they rely on statistical techniques such as panel data regression and Altman Z-score have been widely used to predict financial metrics such as liquidity, financial stability and solvency **(Bandyopadhyay *et al.,* 2023).** However, due to the development of AI, the ML techniques such as Random Forest and gradient boosting have been used to predict the credit risk with accuracy, improving transparency, and this study reveals the importance of decision-making made by the system **(Chang, Victor*, et al.,* 2025).** Additionally, similar studies have explored how the usage of AI and ML techniques, it can increase the potential in credit risk management, operational efficiency in the banks, and reduce the human limitations while comparing the traditional models. (**Baglarbasi, Emel 2025**). Moreover, a major limitation of this study was the dataset of Ethiopian banks, and their focus was only on loans, which may not represent other types of credit products. **(Teklemarkos, Senait 2025).** Comparative studies further suggest that machine learning and Deep learning they supervises and indicate the Early Warning Systems of credit risk, and they perform the decision-making. **(Sarkar, Rajib 2026).**

3. 1 THEORETICAL FRAMEWORK

3.11 Regulatory Pressure Hypothesis Theory (RPH)

The Regulatory intervention has become a significant factor for banking and financial institutions. This study, embedded in RPH, elucidates how the banks align their credit risk financial behaviour in response to regulatory anticipation. And stringent supervisory frameworks. When there is an increase in regulatory scrutiny, it often results in signalled by rise in NPAs. (**Goldbach, R. 2015).** This theory implies that high regulatory scrutiny will promote robust banking performance disclosure and practices and financial sustainability within the banks. However, few studies have explored this association in the context of banking practices by adopting regulatory compliance practices. The present study utilizes Regulatory Pressure Hypothesis (RPH) to investigate the association between Regulatory Pressure and

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Credit Risk management of selected banks in India. (**Mateev, M., Sahyouni, A., & Tariq, M. U. 2023).**

Theory Hypothesis

H_{01}: Regulatory Pressure results in an increase in Provision Coverage Ratio

H_{02}: The increase in Net NPA stimulates Regulatory Pressure.

H_{03}: There is an association between CAR and Regulatory Pressure.

3.2 CONCEPTUAL FRAMEWORK

The study utilizes financial metrics such as Bank size, Capital Adequacy Ratio (CAR), Basel III, Return on Assets (ROA), Cost-to-income ratio (CIR), Provision Coverage Ratio (PCR), which were used as predictor variables and Net NPA was used as the dependent variable. Besides, this research performs a comparative analysis of Econometric and Advanced Machine Learning tools used for the Prediction of Credit Risk of selected banks in India.

3.3 RESEARCH GAP

In the enormous studies, they have used the traditional models such as logistic regression, panel data regression, Linear Discriminant Analysis (LDA), while with the rapid growth of AI, they have used Machine Learning tools, such as Random Forest, and neural networks. However, most of the studies have done each model separately. But limited studies have been used to examine the comparative models in the prediction of Credit Risk in the banking industry. The Empirical evidence from selected commercial banks in India remains limited, particularly regarding the accuracy and practical implications of the comparative models.

3.41 DEVELOPMENT OF HYPOTHESIS

H_{01}: CAR significantly influences Net NPA.

H_{02}: Bank size impacts Net NPA.

H_{03}: Provision Coverage influences Net NPA.

H_{04}: Cost-to-income impacts Net NPA.

H_{05}: Credit Score significantly impacts Net NPA.

H_{06}: ROA significantly influence Net NPA.

3.42 COMPARATIVE PREDICTION OF HYPOTHESIS

H_{07}: AI and ML tools provide higher accuracy than econometric tools.

4.1 RESEARCH METHODOLOGY

The study employs a quantitative methodology and uses secondary data that have been sourced from the Annual reports, RBI website, and Capitaline AWS software for the period of 5 years. It includes 75 observations. The sample size comprises of 15 commercial banks that were operating in India. The comparative study includes panel data regression models, where fixed effects and the Hausman test have been used. Machine Learning models, such as Random Forest and decision trees, provide quick predictions and high accuracy and performance.

4.2 MODEL SPECIFICATION

Panel data Econometric equation

$$\text{Net NPA}_{it} = \alpha + \beta_1 BS_{it} + \beta_2 CTI_{it} + \beta_3 PCR_{it} + \beta_4 CAR_{it} + \beta_5 ROA_{it} + \beta_6 CS_{it} + €_{it}$$

Where:

- Net NPA = dependent variable shows non-performing assets;
- Bs = Bank size, represents the log of Total Assets of the Bank;
- The parameters for $\beta_{1 \text{ to }} \beta_6$ represent the regression coefficients for the estimation of variables
- CTI = Cost-to-income ratio, PCR = Provisional Coverage Ratio, ROA = Return on Assets. All these variables represent the bank's credit score (CS).
- $€_{it=}$ represents ideocratic error term.

The Hausman test is used to compare the Fixed Effect (FE) and Random Effect (RE) of the panel data analysis. It checks the independent variables and individual unobserved facts are correlated, you want to use the Fixed Effect (FE) model, and there is no correlation between variables, we can use the Random Effect (RE).

$H = (\hat{\beta} FE=\beta RE)' [Var \hat{\beta} (RE)]^{-1} (\hat{\beta} FE - \hat{\beta} RE)$.

Non-linear Machine Learning (ML) Mapping

The Panel data regression captures the linear cause and effect of the variables. While the bank metrics often represent non-linear relationships and threshold constraints of the variables.

I. Decision Tree

The data sets are divided into different uniform groups by minimising Mean Squared Error (MSE), which points out for Net NPA.

II. Random Forest

This ML is the advanced version of a decision tree. It is prevented by the creation of multiple individual trees using bootstrapping across panel data. This tool combines the results of multiple individual trees into a single stabilised forecast for forecasting.

$$\hat{f}\ ^{B} RF\ (x)\text{-}1/b \sum_{b-1}^{n} Tb\,(x)$$

It is verified by adjusting R2, Root Mean Squared Error (RME) and Mean Absolute Error (MAE) metrics.

5. ANALYSIS AND INTERPRETATION

1. Descriptive Statistics

The Summary of statistics demonstrates significant findings of the financial wellness of selected commercial banks in India. Table 1, represents Net NPAs have a mean of (2.0%), indicating that the sampled bank maintained relatively strong asset quality. Furthermore, there was a high PCR (80.07%), which indicates that the bank has adopted a conservative capital approach to mitigate credit losses and ensure long-term financial stability. With respect to Solvency, the average of CAR (16.445) met the regulatory requirements of RBI CAR BASEL III norms, demonstrating the robust capital positioning. While the ROA of the mean (0.881%) suggests that reasonable returns were expected during the period of 2020-21 to 2024-25. Regarding the Cost to Income mean (445.5%), suggesting that there was moderation and the standard deviation (16.22) which shows that there was a wide gap in operational efficiency. Finally, bank size (13.38 log form) and credit score (0.49) confirm balanced binary data. within the distribution and the dataset is suitable for econometric analysis.

2. Correlation Matrix

Table 2 demonstrates the Correlation Matrix of the variable. The Net NPA exhibit a moderate negative correlation with Credit Score (0.616) and CAR (0.577), implying that as these variables increase, Net NPA will also tend to increase. It has a weaker positive relationship with Cost to Income (0.308) and bank size (0.353) and an insignificant correlation with provision coverage (0.051). This implies provisioning policy practices were largely decoupled from short-term volatility in NPAs within the selected sample. The ROA indicates that (-0.507) shows a negative correlation with NPA. When the profitability of the bank increases, the Net NPA will decrease.

Among the predictor variables, CAR Basel III is moderately correlated with provision coverage (0.430) and cost to income (0.407), implying some independence. The other correlations were low to moderate, not exceeding 0.7, indicating no serious multicollinearity issue. Therefore, the datasets were considered statistically reliable for conducting Fixed Effect regression analysis without coefficient instability.

3. Panel Data Regression & Hausman test

The panel data Table 3 showed that the Capital Adequacy Ratio (CAR) had a significant negative relationship between Net NPA (β= -0240; p=0.0010 <0.05). Therefore, the null hypothesis was rejected, denoting that a higher Capital Adequacy Ratio results in a reduction in non-performing assets. Similarly, the Provisional Coverage Ratio has shown that there was a Significant negative relationship between Net NPA (β= -0.089; p=0.0025<0.05), indicating that the Bank has maintained good provision, which results in reducing the NPA and the credit risk and the null hypothesis was rejected. ROA exhibits a statistically significant negative relationship with Net NPA (β= -0.478; p=0.008<0.05), indicating that higher profitability of a bank will result in lower NPA. However, Bank size (β= -0.647; p=0.1953 > 0.05), Cost-income ratio (β= -0.012; p=0.479>0.05) and Credit score (β=0.2077> p=0.0018) were found to have no Significant relationship between Net NPA. Hence, the null hypothesis was accepted.

The Hausman test result (χ^2 = 20.3279, p = 0.0024) implies that the fixed effects model was more appropriate than the Random effects model. The fixed effects regression shows that CAR Basel III (β = −0.2405, p < 0.01) and provision coverage ratio (β = −0.0890, p < 0.01) have a significant negative impact on Net NPA. The ROA exhibits a statistically significant negative relationship with Net NPA in a fixed effect model (β = −0.478, p < 0.018). This result indicates that an increase in capital adequacy and stronger provisioning policies and ROA may strengthen the banks' asset quality and profitability of the banks. . The model explains about 78% of the variation in Net NPA, and the overall model was statistically significant.

MACHINE LEARNING MODELS

I. DECISION TREE.

This figure demonstrates that CAR Basel III and Provision coverage were the primary variables that influenced the outcome. The CAR Basel III was below -0.098 and the provision coverage was very low -0.78. The outcome was classified as 0 (n=17), whereas a relatively higher value (above 0.78) means the outcome becomes 1 (n=8). However, when CAR Basel III is above -0.098, the model directly predicts outcome (n=23) without considering other variables. Overall, this model indicates that CAR Basel III plays a definitive role and provision coverage acts as a secondary factor if the CAR values are lower.

II Random Forest

To evaluate the prediction of Random Forest for the credit risk, Table 5. shows that 75 panel data observations have been divided into (n=48), validation (n=12) and test (n=15) subsets. The enhancement framework has proven to be highly adaptive, showing no sign of overfitting. The refined model has achieved validation accuracy of 83.3% and a test accuracy of 66.7%. The minimal drop in accuracy between validation and out-of-sample testing model represents the model's reliability and its ability to accurately predict risk threshold without overfitting.

COMPARISON OF ECONOMETRIC AND MACHINE LEARNING TECHNIQUES

The variables such as Net NPA CAR, provision coverage ratio, cost-income ratio, bank size, ROA and credit score plays a significant role in the prediction of credit risk in the Indian banks. The traditional model, such as the panel data regression model, results reveal a significant negative impact on Net NPA, implying that stronger capital adequacy and higher provisioning reduce credit risk in banks. Furthermore, Machine Learning models such as Random Forest result shows 80% accuracy compared to the Decision Tree model. This study suggests that machine learning models are used to predict better than traditional statistical models and also provide quick decision-making.

7. DISCUSSION

7.1 Estimation of Hypothesis

Based on Fixed Effects Regression, we evaluate the following results

H_{01}: CAR significantly influences Net NPA.

The **Table 4** Panel data regression analysis shows that a Significant negative relationship exists between CAR and Net NPA (β= -0240; p=0.0010 <0.05). This result suggests that a higher Capital Adequacy Ratio (CAR) will reduce Non-Performing Assets (NPA) of banks. Hence, the null hypothesis was rejected.

H_{02}: Bank size impacts Net NPA.
The Sample size of banks does not impact the change in Net NPAs. The calculated value (β= -0.647; p=0.1953 > 0.05), the result is greater than the significance value, the alternative hypothesis is rejected, and the null hypothesis is accepted.
H_{03}: Provision Coverage influences Net NPA.
This variable shows a (β = -0.089; p=0.0025<0.05) suggesting that it is statistically significant at 5% it shows a strong predictor that maintaining a provision not only meets the regulatory requirements of the bank but also impacts the financial stability of the bank. Thus, there is an association between the Provisional Coverage Ratio (PCR) and Net NPA.
H_{04}: Cost-to-Income impacts Net NPA.
Cost-to-Income ratio does not have an Impact on Net NPA (β = -0.012; p=0.479>0.05). Since the significant value is much greater than the p-value, the alternative hypothesis is rejected, and the null hypothesis is accepted. Thus, the operational efficiency of the banks does not impact the Net NPA.
H_{05}: Credit score influences Net NPA.
The Credit score, which contains the binary value of the variable. (β=0.2077> p=0.0018) Here, the computed value was much greater than the significance value; the null hypothesis is accepted. Thus, the credit score does not influence Net NPA.
H_{06}: ROA impacts Net NPA.
Return on Assets (ROA) exhibits a statistically significant negative relationship with Net NPA (β= -0.478; p=0.008<0.05), indicating that higher profitability of a bank will result in lower NPA.

7.2 Comparative Performance of Econometric analysis and AI-models:

H_{07}: AI and ML tools provide Higher Accuracy than Econometric tools.
Based on the evidence, the comparison of AI-ML tools vs traditional econometric tools suggests that while traditional models provide highly reliable results for regulatory requirements and financial stability of banks. Machine learning tools provide superior predictive insights and offer higher accuracy than conventional models.
The Random Forest Model has attained a higher level of accuracy 80% followed by the Decision Tree analysis at 73.3%. In contrast to linear panel data regression, the Decision Tree have spotted the CAR ratio and Provision Coverage Ratio (PCR) exhibit a non-linear pattern to predict the outcome.

8. CONCLUSION

8.1 Summary of findings

This study aims to compare the predictive efficiency of Artificial Intelligence models and traditional statistical models in credit risk for selected commercial banks in India. Overall findings of the study reveal that AI-based models, such as Random Forest and decision tree analysis, enable the prediction of complex data with higher and quicker decision-making compared to traditional econometric modelling. However, econometric modelling is a foundational model widely accepted by regulatory bodies and used across various sectors in the economy.
The findings of the study indicate that banks have to adopt a hybrid model combination of AI and statistical models, to enhance higher prediction, make the decision-making faster, provide transparency, superior accuracy and meet regulatory requirements of the banks.

9. LIMITATIONS

- **Sample size:** The study focused only on 15 selected Commercial banks in India and may not consider the entire Banking industry in the economy.

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- **Time period:** The study was confined to the limited period of 5 years from (2020-21to 204-25), and findings must vary across different financial years.
- **Variables:** The study has chosen the particular variables, and it may not cover other macro economic variable such as GDP Percapita, Inflation rate, and bank interest rates, which were excluded.
- **Traditional Model constraints:** This study has utilised Traditional econometric models such as panel data regression, along with the Hausman Test. This reveals that the Fixed Effect Model focuses on only time variant and not the dynamic changes of the bank.
- **Absence of Developed models of AI-ML:** The study covers a very limited and basic set of AI-ML models to perform a comparative evaluation with Econometric models, and does not cover advanced tools for the prediction of the Credit crisis of the banks in India.

10. SCOPE FOR FUTURE RESEARCH

The present study is bound by certain constraints that can provide the scope and enrich your future research. First, the study contains a limited sample size within the Indian banking sector. Further, it can expand the sample size by including the private sector, public sector, and also foreign banks for broader and meaningful research. Second, the analysis covers a very limited and specific time period for five years, future may extend to broaden your horizon to get long-term credit risk for different financial periods. Third, there was a variable constraint in this study; for further research, use macro-economic tools such as GDP, Inflation, unemployment rate, and per capita income to get an elucidative outcome. Furthermore, we can not only use econometric tools such as Panel data regression, but also we can use advanced methods like the Granger Causality Test, Generalised Method of Moments (GMM) approach, and Panel Vector Autoregression (PVAR) methods. Conclusively, this analysis of Artificial Intelligence and Machine Learning (AI-ML) models excludes the advanced tools for prediction, such as Neural Networks, hybrid econometric AI models, and XG Boost. Future research integrates advanced AI-ML techniques for the prediction and forecasting of the credit risk of banks.

TABLES

Table:1 DESCRIPTIVE STATISTICS

STATISTICS	NET NPA	PROVISION COVERAGE	CREDIT SCORE	COST TO INCOME	BANK SIZE	ROA	CAR BASEL
Observations	75	75	75	75	75	75	75
Mean	2.003	80.07	.49	45.56	13.38	.8815	16.445
Std. deviation	1.70	10.45	.503	16.22	1.11	1.125	2.983
Minimum	.27	50.31	0	.00	10.62	-2.95	8.50
Maximum	7.6	96.85	15.7	74.40	15.72	5.39	27.43
Variance	2.92	109.31	.253	263.35	1.248	1.266	8.900

(source: Secondary data)

Table 2: CORRELATION MATRIX

NET NPA	CAR BASEL	COST INCOME	PROVISION COVERAGE	BANK SIZE	CREDIT SCORE	ROA
1	0.576	0.30	0.050	0.353	0.61	-0.507
0.576	1	0.407	0.430	0.075	0.399	0.493
0.308	0.407	1	0.172	0.242	0.256	-0.223
0.050	0.430	0.172	1	0.341	0.059	-0.217
0.353	0.075	0.242	0.341	1	0.255	0.202
0.616	0.399	0.256	0.059	0.255	1	-0.243

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(source: Secondary data)

TABLE 3: PANEL DATA REGRESSION

Statistics	Constant	Bank size	CAR	PCR	CIR	Credit Score	ROA
Coefficient	22.300	-0.647	-0240	-0.089	-0.012	0.413	-0.478
Standard Error	5.590	0.490	0.069	0.028	0.017	0.323	0.1478
t-statistic	3.95	-1.310	-3.460	-3.170	-0.710	1.270	-3.240
p-value	0.0002	0.195	0.0010	0.0025	0.479	0.207	0.0018
Significance	Significan t	Not significant	Signi ficant	Significan t	Not significant	Not significant	Signi ficant

(source: Secondary data)

Table 4: MODEL STATISTICS

STATISTIC	VALUE
R^2	0.780
Adjusted R^2	0.698
F- statistic	9.58
observation	75
Cross section	15 banks
period	2020-24

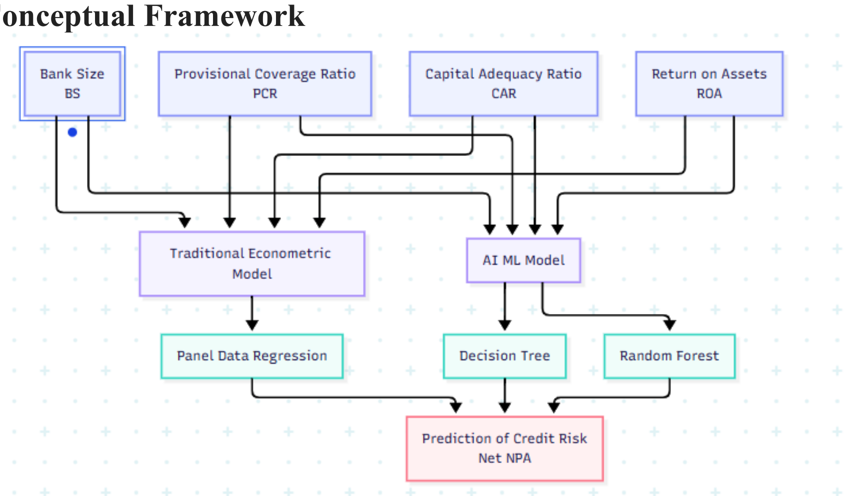
(source: Secondary data)

I. Table 5 : RANDOM FOREST

MODEL	TREE	FEATURES PER SPLIT	VALIDATION ACCURACY	TEST ACCURACY	OOB ACCURACY
Decision	-	-	0.750	0.733	-
Random forest	36	2	0.833	0.800	0.667

(source: Secondary data)

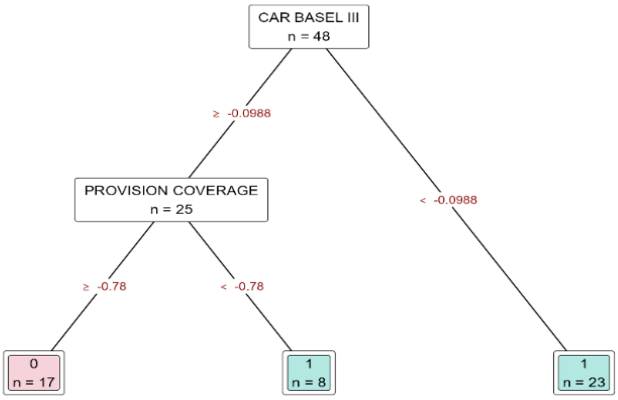
Figure _1 : Conceptual Framework



(Figure_1)

Figure_2 – ANALYSIS AND INTERPRETATION

Machine Learning Models



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