

Predictive Analytics for Credit Risk Assessment: A Data-Driven Approach to Improving Credit Decision-Making

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Abstract- This article discusses the role of predictive analytics in credit risk assessment. It explains how organizations can use historical customer and financial data to predict loan default, improve credit decisions, reduce financial losses, and strengthen risk management. The discussion is generalized and does not refer to any specific company. Statistical techniques such as descriptive analysis, t-test, chi-square test, and ANOVA are highlighted along with factors including credit score, annual income, debt-to-income ratio, employment experience, previous defaults, and loan purpose.

Keywords: Predictive Analytics, Credit Risk, Credit Scoring, Machine Learning, Financial Analytics, Loan Default

I. INTRODUCTION

Predictive analytics combines statistics, data mining and machine learning to forecast future outcomes using historical data. Financial institutions increasingly rely on predictive models to evaluate borrower behaviour, identify risky applicants and improve lending decisions. Traditional credit evaluation often depends on manual judgment, whereas predictive analytics provides objective, data-driven insights that improve consistency and accuracy. Predictive analytics combines statistics, data mining and machine learning to forecast future outcomes using historical data. Financial institutions increasingly rely on predictive models to evaluate borrower behaviour, identify risky applicants and improve lending decisions. Traditional credit evaluation often depends on manual judgment, whereas predictive analytics provides objective, data-driven insights that improve consistency and accuracy. Predictive analytics combines statistics, data mining and machine learning to forecast future

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II. LITERATURE REVIEW

Previous research by Altman, Thomas, Hand, Henley, Baesens, Brown, Lessmann, Yeh and others shows that statistical and machine learning techniques significantly improve credit scoring accuracy. Logistic regression, decision trees, neural networks and support vector machines have consistently demonstrated better prediction performance than traditional judgment-based methods. Previous research by Altman, Thomas, Hand, Henley, Baesens, Brown, Lessmann, Yeh and others shows that statistical and machine learning techniques significantly improve credit scoring accuracy. Logistic regression, decision trees, neural networks and support vector machines have consistently demonstrated better prediction performance than traditional judgment-based methods. Previous research by Altman, Thomas, Hand, Henley, Baesens, Brown, Lessmann, Yeh and others shows that statistical and machine learning techniques significantly improve credit scoring accuracy. Logistic regression, decision trees, neural networks and support vector machines have consistently demonstrated better prediction performance than traditional judgment-based methods. Previous research by Altman, Thomas, Hand, Henley, Baesens, Brown, Lessmann, Yeh and others shows that statistical and machine learning techniques significantly improve credit scoring accuracy. Logistic regression, decision trees, neural

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III. OBJECTIVES:

- Identify factors influencing loan default.
- Understand the impact of income, credit score, debt-to-income ratio and previous defaults on repayment behaviour.

IV. RESEARCH METHODOLOGY

The study adopts a descriptive and analytical research design using secondary data. Common statistical tools include percentage analysis, descriptive statistics, chi-square test, independent sample t-test and ANOVA. Customer variables include annual income, employment experience, credit score, debt-to-income ratio, loan purpose, previous defaults and repayment status. The study adopts a descriptive and analytical research design using secondary data. Common statistical tools include percentage analysis, descriptive statistics, chi-square test, independent sample t-test and ANOVA. Customer variables include annual income, employment experience, credit score, debt-to-income ratio, loan purpose, previous defaults and repayment status. The study adopts a descriptive and analytical research design using secondary data. Common statistical tools include percentage analysis, descriptive statistics, chi-square test, independent sample t-test and ANOVA. Customer variables include annual income, employment experience, credit score, debt-to-income ratio, loan purpose, previous defaults and repayment status. The study adopts a descriptive and analytical research design using secondary data. Common statistical tools include percentage analysis, descriptive statistics, chi-square test, independent sample t-test and ANOVA. Customer variables include annual income, employment experience, credit score, debt-to-income ratio, loan purpose, previous defaults and repayment status. The study adopts a descriptive and analytical research design using secondary data. Common statistical tools include percentage analysis, descriptive statistics, chi-square test, independent sample t-test and ANOVA. Customer variables include annual income, employment experience, credit score, debt-to-income ratio, loan purpose, previous defaults and repayment status. The study adopts a descriptive and analytical research design using secondary data. Common statistical tools include percentage analysis, descriptive statistics, chi-square test, independent sample t-test and ANOVA. Customer variables include annual income, employment experience, credit score, debt-to-income ratio, loan purpose, previous defaults and repayment status.

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V. DISCUSSION

Analysis generally indicates that customers with lower credit scores, higher debt burdens and previous defaults have greater probabilities of loan default. Higher annual income and stable employment are associated with improved repayment capacity. Loan purpose also influences repayment behaviour. Predictive analytics enables early identification of high-risk borrowers, faster decisions and improved portfolio management. Analysis generally indicates that customers with lower credit scores, higher debt burdens and previous defaults have greater probabilities of loan default. Higher annual income and stable employment are associated with improved repayment capacity. Loan purpose also influences repayment behaviour. Predictive analytics enables early identification of high-risk borrowers, faster decisions and improved portfolio management. Analysis generally indicates that customers with lower credit scores, higher debt burdens and previous defaults have greater probabilities of loan default. Higher annual income and stable employment are associated with improved repayment capacity. Loan purpose also influences repayment behaviour. Predictive analytics enables early identification of high-risk borrowers, faster decisions and improved portfolio management.

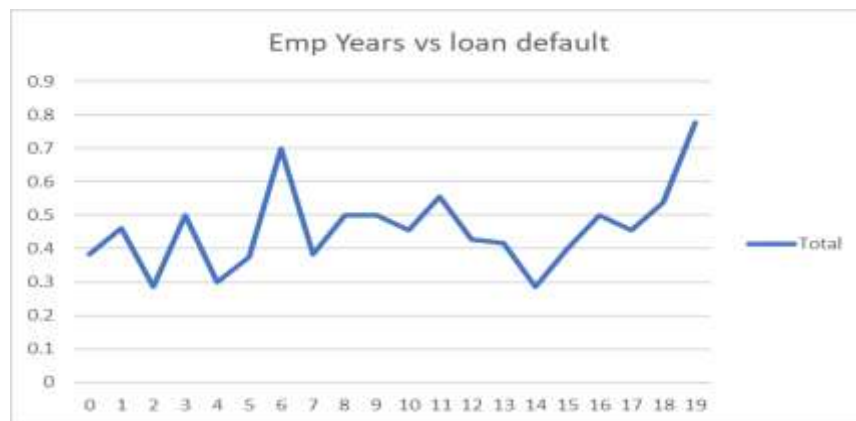
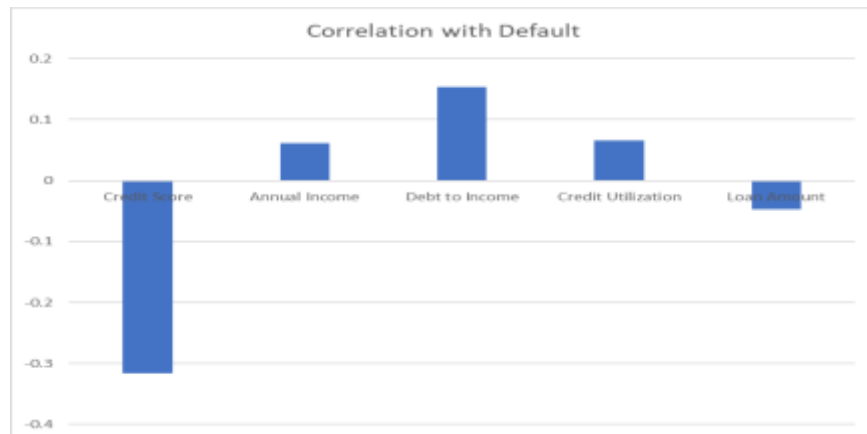
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VI. FINDINGS

Credit score, debt-to-income ratio, annual income and previous default history are among the strongest predictors of credit risk. Statistical tests generally support significant relationships between these variables and loan default. Data-driven decision making improves customer classification and reduces lending risk. Credit score, debt-to-income ratio, annual income and previous default history are among the strongest predictors of credit risk. Statistical tests generally support significant

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VIII. CONCLUSION

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REFERENCES

- [1] Han, J., Kamber, M., & Pei, J. (2012). Data Mining: Concepts and Techniques. 3rd Edition. Morgan Kaufmann Publishers.
- [2] Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate Data Analysis. 8th Edition. Cengage Learning.
- [3] Gupta, S. P. (2021). Statistical Methods. Sultan Chand & Sons.
- [4] Kothari, C. R., & Garg, G. (2019). Research Methodology: Methods and Techniques. New Age International Publishers.
- [5] Altman, E. I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *Journal of Finance*, 23(4), 589–609.
- [6] Siddiqi, N. (2017). Intelligent Credit Scoring: Building and Implementing Better Credit Risk Scorecards. 2nd Edition. John Wiley & Sons.