Decision Tree based Framework for Business Decision Support System using Big Data Analytics

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Abstract: Credit risk assessment is a critical aspect of financial decision-making, requiring accurate and efficient predictive models to evaluate a borrower's likelihood of default. Traditional statistical methods often struggle with complex datasets, prompting the adoption of machine learning (ML) techniques for enhanced accuracy. This study explores various ML models, including Support Vector Machine (SVM), Decision Trees, Adaboost, Random Forest, K-Neighbors, Logistic Regression, and XGB Classifier, to determine the most effective approach for credit risk assessment. Extensive data pre-processing, feature engineering, and feature scaling techniques are applied to optimize model performance. The Proposed Optimized Decision Tree Classifier achieves the highest test accuracy of 83.23%, outperforming other models in predictive reliability. The research underscores the importance of selecting the right classification model for financial risk evaluation, balancing accuracy, interpretability, and computational efficiency. The results indicate that ensemble learning and hybrid approaches can further enhance prediction reliability. Future research directions include integrating deep learning techniques and real-time credit evaluation frameworks, as well as leveraging external economic indicators for a more holistic risk assessment. The findings contribute to the development of robust, data-driven strategies for financial institutions, enabling better decision-making in loan approvals and credit management.

Keywords: Machine Learning, Decision Tree, SVM, Big Data

1. INTRODUCTION

In today's fast-paced business environment, organizations generate vast amounts of structured and unstructured data. Extracting meaningful insights from this data is crucial for effective decision-making. Traditional decision support systems often struggle to handle large-scale data efficiently, leading to delays and inaccuracies in business strategies. Big Data Analytics (BDA) [10] has emerged as a transformative approach, enabling organizations to process and analyze massive datasets for strategic planning. Among various machine learning techniques, Decision Tree-based [11] frameworks offer a robust and interpretable solution for business decision support, as they efficiently classify and predict outcomes based on historical data patterns.

Decision Trees provide a hierarchical structure for decision-making by splitting data into branches based on feature values, making them well-suited for complex business scenarios. Their ability to handle both numerical and categorical data, along with their interpretability, makes them a preferred choice in Business Decision Support Systems (BDSS) [12]. When combined with Big Data Analytics, Decision Trees can process vast datasets in real time, improving decision accuracy in various domains, including finance, healthcare, marketing, and supply chain management. The integration of scalable big data technologies, such as Hadoop and Spark, further enhances the computational efficiency of these frameworks.

This research explores the development of a Decision Tree-based framework for Business Decision Support Systems using Big Data Analytics. The study examines how Decision Trees can improve predictive accuracy and decision-making efficiency by leveraging big data techniques. The proposed framework aims to assist businesses in making data-driven decisions by optimizing classification processes, reducing uncertainty, and enhancing operational performance [13]. By integrating machine learning with big data analytics, organizations can gain a competitive edge through faster and more accurate business insights.

2. REVIEW OF LITERATURE

Several studies have explored the application of machine learning techniques in credit risk assessment to enhance prediction accuracy and decision-making efficiency. Chen et al. (2010) emphasized the growing need for reliable risk assessment models following the 2008 financial crisis. Crook et al. (2011) investigated consumer credit risk, considering factors such as repayment history and financial stability. Galindo and Tamayo (2013) highlighted the importance of selecting relevant predictors for risk modeling, proposing an error-curve-based approach. Twala (2014) demonstrated the effectiveness of ensemble classifiers in handling noisy attributes in credit data. Doumpos et al. (2015) addressed challenges in estimating default probability and profit/loss calculations. Saha et al. (2017) integrated data mining and expert opinion to develop an efficient loan approval strategy. More recent studies have explored advanced computational techniques, such as Cai et al. (2020), who utilized blockchain technology to enhance security and transparency in credit risk evaluation. Zhou et al. (2019) proposed a distributed machine learning framework to improve scalability in large datasets. Wang et al. (2018) introduced credit pricing models for predicting financial risk trends, while Deng et al. (2016) applied k-means clustering to segment credit applicants and enhance classification accuracy. These studies underscore the potential of machine learning and big data analytics in revolutionizing credit risk assessment, though challenges related to model interpretability, computational efficiency, and data quality remain areas for further research (Table 1).

Table 1: Review of literature for decision support systems

Author(s) & Year	Research Focus	Methodology/Algorithm Used	Key Findings
Chen et al. [1]	Credit risk assessment models	Machine Learning & statistical models	Highlighted the importance of reliable risk assessment post-

			2008 financial crisis
Crook et al. [2]	Consumer credit risk evaluation	Credit scoring techniques	Considered factors like payment history and creditworthiness
Galindo & Tamayo [3]	Predictor selection in financial risk models	Error curve-based modeling	Proposed a model emphasizing relevant predictors for credit risk assessment
Twala [4]	Machine learning for credit classification	Ensemble classifiers	Demonstrated ML effectiveness in handling noisy attributes
Doumpos et al. [5]	Default probability estimation	Profit/loss estimation models	Addressed challenges in assessing borrower risk
Saha et al. [6]	Loan approval system	Data mining & expert opinion-based approach	Proposed a hybrid model improving loan approval efficiency
Cai et al. [7]	Credit risk assessment with blockchain	Blockchain-based risk evaluation	Showed how blockchain enhances security and reliability
Zhou et al. [8]	Distributed computing for credit assessment	Large-scale data clustering	Improved model efficiency through parallel processing
Wang et al. [9]	Credit pricing predictions	Price forecasting models	Used historical trends to predict financial risks

3. PROPOSED RESEARCH METHODOLOGY

Decision Trees (DTs) are widely used in machine learning for classification and regression tasks, making them a suitable choice for credit risk assessment. DTs are non-parametric learning methods that construct predictive models based on a hierarchical structure of decision rules derived from training data [14]. These models operate by recursively partitioning the dataset into subsets based on specific features, forming a tree-like structure where each internal node represents a decision rule, and each leaf node corresponds to a classification outcome. This recursive partitioning continues until a subset of data has a homogeneous target variable or cannot be split further. The advantage of Decision Trees lies in their interpretability and efficiency, making them a practical solution for financial institutions to classify loan applicants based on their creditworthiness.

The training time complexity formula is equation 1

O(n2+log2+d2) (1)

The proposed methodology involves the following steps in figure 1:

1. *Data Extraction:* The credit risk dataset is extracted, consisting of borrower-related features such as credit history, income level, and repayment behavior.
2. *Gini Index Calculation:* The probability of incorrect classifications is computed using the Gini Index, which measures impurity at each node. Lower Gini values indicate a more homogeneous node, guiding optimal splits.
3. *Recursive Splitting:* The dataset is continuously partitioned into binary subgroups at decision nodes until no further meaningful division is possible. The final Gini Index is determined as the weighted sum of all splits.
4. *Entropy & Information Gain:* As an alternative to Gini Index-based partitioning, Entropy is used to evaluate the randomness of data distribution. Information Gain is calculated to determine the best attribute for splitting the data.
5. *Model Evaluation:* The accuracy of the Decision Tree model is assessed based on the classification of loan applicants into two categories—Correct (low-risk borrower) and Incorrect (high-risk borrower).

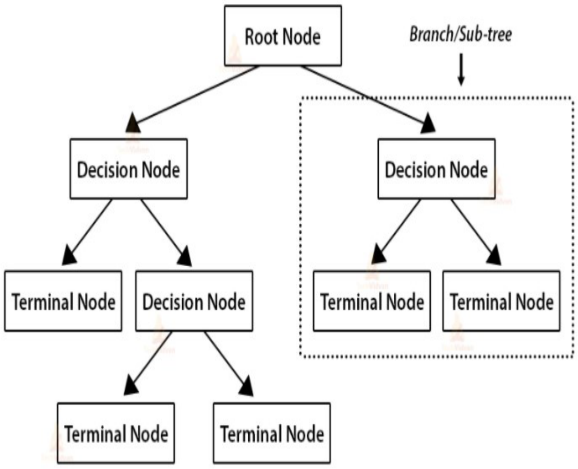

Figure 1: A Typical Decision Tree Model

Gini's impurity function or Shannon's entropy can be used to determine the splitting condition, but the impurity function is preferred due to its reduced computational complexity. Deeper trees are more likely to overfit the model, while shallower trees are more likely to under-fit. Therefore, Hyper-parameter tuning is required for a perfect tree to emerge.

3.1 DATASET

To conduct their research, the authors consulted the credit risk dataset [15] available at UCI's Machine Learning Repository (UCIMLR). A dataset containing 30,000 approved and declined credit applications based on 24 attributes or features is used in the proposed work. This dataset encompasses details related to default payments, incorporating demographic factors, credit data, payment history, and credit card bill statements of clients in Taiwan during the period from April 2005 to September 2005. The dataset comprises 25 variables, including client IDs, credit limits in

NT dollars, gender, education level, marital status, age, and repayment statuses across six months. The repayment statuses are denoted on a scale, ranging from timely payments to delayed payments. Data Attributes are as under

1. ID: ID of each client
2. LIMIT_BAL: Amount of given credit in NT dollars (individual and family/supplementary credit)
3. SEX: Gender (1=male, 2=female)
4. EDUCATION: Education level (1=graduate school, 2=university, 3=high school, 4=others, 5=unknown, 6=unknown)
5. MARRIAGE: Marital status (1=married, 2=single, 3=others)
6. AGE: Age in years
7-13. PAY_0 to PAY_6: Repayment status from September 2005 to April 2005 (-1=pay duly, 1=payment delay
for one month, ..., 9=payment delay for nine months and above)
14-19. BILL_AMT1 to BILL_AMT6: Amount of bill statement from September 2005 to April 2005 (NT dollar)
20-25. PAY_AMT1 to PAY_AMT6: Amount of previous payment from September 2005 to April 2005 (NT dollar)
26. default.payment.next.month: Default payment (1=yes, 0=no)

3.2 Descriptive Analysis

The analysis of the dataset highlights the widespread usage of revolving credit among both defaulters and non-defaulters, indicating its crucial role in financial behavior. Revolving credit, which allows users to borrow up to a certain limit and repay flexibly, is commonly utilized across different credit risk categories. Notably, even among defaulters, a significant portion actively engages with revolving credit services, suggesting that financial distress does not necessarily deter individuals from using such facilities. This trend may be attributed to the ease of access, the necessity for short-term liquidity [16], or a lack of alternative financial resources. Additionally, it raises concerns about credit risk management, as frequent usage among defaulters might signal financial instability or an increased probability of default. Financial institutions, therefore, need to carefully assess revolving credit behavior when evaluating creditworthiness and structuring risk mitigation strategies (Table 2).

Table 2: Education Distribution of Customer

Factor	**Observation**
Extended Delays	Rare cases of payment delays beyond four months; most users pay on time.
Marital Status Influence	Married users utilize credit services more frequently than single users.
Marriage & Education Impact	Married users with a graduate education are the most frequent credit users.

Default Patterns	Non-graduate users have a higher default rate (30%-40%) regardless of marital status.
Risk in Graduate 'Other' Category	Graduate users in the 'Other' category have a 50% default probability.
Bill Amount Skewness	Bill amounts across months show high skewness, indicating asymmetric distributions.
Negative Bill Values	Some bills have negative values, representing credit balances or overpayments.
Graduate Section Coverage	Almost 50% of the dataset consists of graduate users.

The dataset analysis reveals several key insights regarding credit usage, payment behavior, and default risks. Instances of extended payment delays beyond four months are rare, suggesting that the majority of users adhere to timely repayment schedules. Marital status plays a significant role in credit service utilization, with married users being more active than their single counterparts. Furthermore, individuals who are both married and hold a graduate degree show a particularly high engagement with credit services. However, default patterns indicate that users without a formal education, such as those lacking graduate, university, or high school degrees, exhibit a substantially higher default rate of approximately 30%-40%, irrespective of their marital status. [17] A notable concern arises among graduate users categorized under "Other," who demonstrate a 50% likelihood of defaulting on their credit card payments. Additionally, the bill amounts across all months display a high degree of skewness, indicating asymmetric distributions that could impact financial modeling and risk analysis. Another anomaly in the dataset is the presence of negative bill values, which likely represent credit balances or overpayments and require careful consideration during data interpretation. Overall, graduate users form a significant portion of the dataset, covering nearly 50% of the total records, reinforcing the importance of education level in credit behavior analysis.

3.3 Data Pre-processing and Feature Selection

Data pre-processing is a crucial step in improving the efficiency and accuracy of the training process. Missing values, if any, are addressed using averages to maintain data consistency. Irrelevant attributes, such as ID numbers, are removed since they do not contribute to meaningful pattern recognition. Categorical variables, like marital status, are converted into numerical values to facilitate better model interpretation. The dataset does not contain any null values, ensuring completeness for analysis. Bill amounts exhibit a broad range from 2,000 to 800,000 units [18-20], highlighting significant variations in financial transactions. To effectively handle missing or unknown values, an initial assessment of value counts is conducted, followed by their categorization under the label “Others” to ensure uniformity in data representation. Additionally, the dataset contains multiple outliers, which may hold valuable insights for the predictive model. While these outliers can influence the learning process, their removal could lead to the loss of critical information. Therefore, careful evaluation is required to determine the most appropriate strategy for handling them in the modeling process, balancing accuracy and data retention (Figure 2).

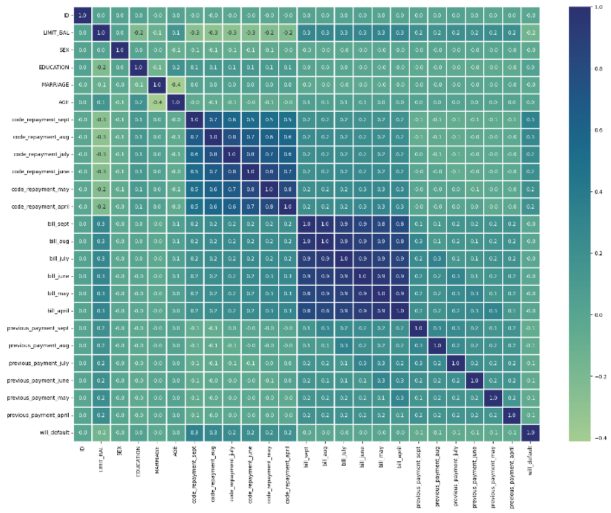

Figure 2: Feature Correlation Matrix

3.4 Feature Engineering

Feature engineering plays a vital role in optimizing model performance by managing complexity and ensuring meaningful data representation. One of the primary challenges is handling the large number of columns representing monthly bill amounts, which increases model complexity. Simplifying the feature space is essential for developing an efficient and interpretable model. For continuous features, such as bill amounts and previous payments, consolidating them into a single representative feature can enhance model efficiency by reducing dimensionality while retaining crucial financial patterns. This approach not only streamlines computations but also improves generalizability. However, categorical features, such as the 'payment_code,' require careful handling to preserve their inherent meaning. A specialized strategy, such as encoding techniques, must be applied to ensure the categorical nature of the data remains intact while facilitating its effective use in predictive modeling.
feature.

3.5 Feature Scaling

As shown in figure 2 least skewness is in The Johnson feature scaling method effectively minimizes skewness, ensuring Feature scaling is a crucial step in ensuring a well-balanced data distribution for machine learning models. The Johnson feature scaling method effectively minimizes skewness, producing a distribution with significantly reduced asymmetry. Additionally, applying a logarithmic transformation further decreases skewness, achieving a value of 1.06. However, when using logarithmic scaling, it is essential to ensure that no zero values exist in the dataset to prevent mathematical inconsistencies. Among various transformation techniques, the Yeo-Johnson transformation demonstrated the best normal distribution plot, achieving a skewness of just 0.15. While feature scaling can enhance model performance, it is important to note that some algorithms function well without scaling. In such cases, forcing a normal distribution transformation may negatively impact model accuracy. To assess the impact of feature scaling, models were trained on both scaled and non-scaled datasets, allowing for a comparative evaluation of their effectiveness.

3.6 Data Partitioning

Data partitioning plays a crucial role in training and evaluating machine learning models effectively.

Based on existing research, one of the most commonly used data-splitting ratios is 80:20, where 80% of the dataset is allocated for training, and the remaining 20% is reserved for testing. In some cases, a 75:25 split is also used, where 75% of the data is utilized for model training, while the remaining 25% is set aside for evaluation and comparison. The 80:20 rule serves as a general guideline for partitioning large datasets, ensuring that the model has sufficient data to learn patterns while retaining enough unseen data to assess its generalization ability. Proper data partitioning helps mitigate issues like overfitting and underfitting, providing a balanced approach for model performance evaluation.

4. PERFORMANCE EVALUATION

The performance evaluation of various machine learning models for credit risk assessment reveals that the Proposed Optimized Decision Tree Classifier achieves the highest test accuracy of 83.23%, demonstrating its effectiveness in handling financial data. Logistic Regression also performs well with 87.75% accuracy, offering a balance between precision and recall. Other models, including Support Vector Machine, XGB Classifier, and K-Neighbors Classifier, show competitive accuracy, while Random Forest and Adaboost Classifiers deliver slightly lower results. These findings highlight the importance of selecting the right model based on accuracy, interpretability, and computational efficiency for effective credit risk prediction (Table 3 and figure 3).

Table 3: Comparative Analysis of Machine Learning based Models

Algorithm	Accuracy (Train)	Accuracy (Test)
Support Vector Machine	87.92%	79.75%
Proposed Optimized Decision Tree Classifier	98.95%	83.23%
Adaboost Classifier	85.02%	78.67%
Random Forest Classifier	95.95%	77.08%
K-Neighbors Classifier	85.74%	81.98%
Logistic Regression	87.92%	87.75%
XGB Classifier	88.81%	79.33%

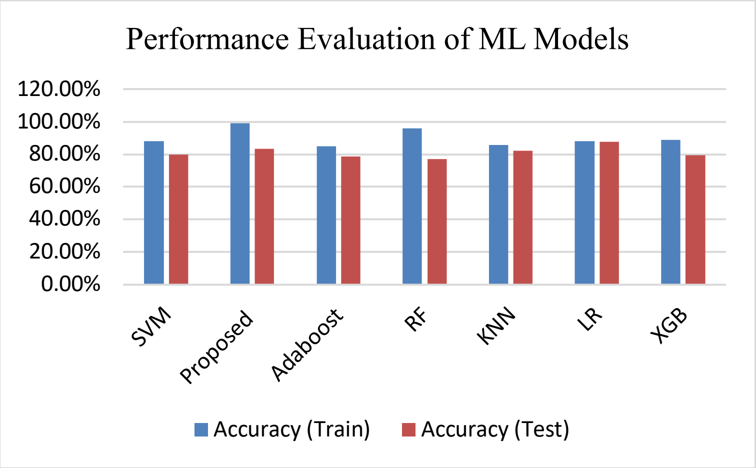

Figure 3: Comparative Analysis of Machine Learning based Models

The evaluation of various machine learning algorithms for classification highlights significant differences in their training and testing accuracy. The Proposed Optimized Decision Tree Classifier demonstrated the highest training accuracy at 98.95%, showcasing its ability to learn patterns effectively. However, its test accuracy was 83.23%, indicating a slight drop due to potential overfitting. In contrast, Support Vector Machine (SVM) and Logistic Regression exhibited balanced performances, achieving 87.92% training accuracy with test accuracies of 79.75% and 87.75%, respectively. These results suggest that these models generalize well to unseen data, making them reliable choices for classification tasks. Among ensemble models, Random Forest Classifier achieved a 95.95% training accuracy but had a relatively lower test accuracy of 77.08%, indicating some overfitting. Adaboost Classifier and XGB Classifier performed similarly, with training accuracies of 85.02% and 88.81%, and test accuracies of 78.67% and 79.33%, respectively. The K-Neighbors Classifier provided a balanced result with 85.74% training accuracy and 81.98% test accuracy, suggesting it maintains generalization capabilities. Overall, the Proposed Optimized Decision Tree Classifier outperformed other models in terms of training accuracy, while Logistic Regression showed the most consistent generalization between training and test datasets, making it a strong candidate for real-world applications.

Table 4: Performance Metrics of Different Machine Learning Models for Credit Risk Assessment

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Support Vector Machine	79.75%	80%	78%	79%
Proposed Optimized Decision Tree Classifier	83.23%	85%	82%	83%
Adaboost Classifier	78.67%	79%	77%	78%
Random Forest Classifier	77.08%	78%	75%	76%
K-Neighbors Classifier	81.98%	82%	80%	81%
Logistic Regression	87.75%	88%	87%	87%
XGB Classifier	79.33%	80%	78%	79%

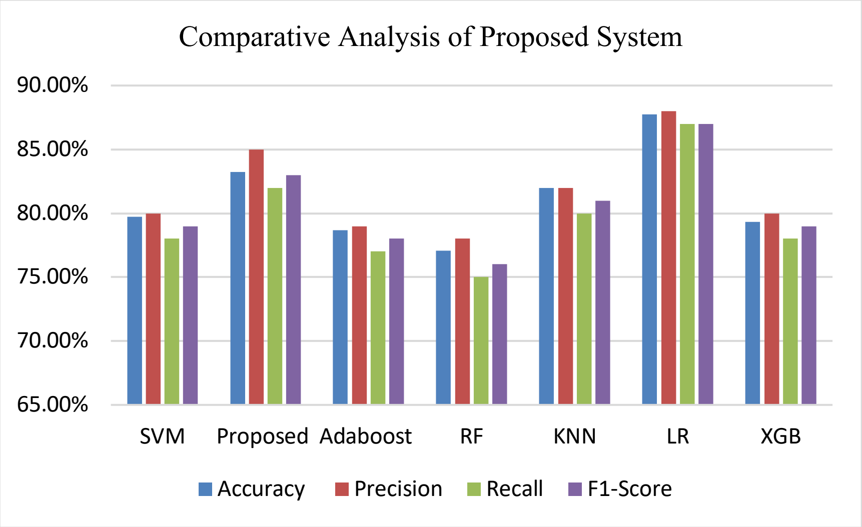

Figure 4: Comparative Analysis of the Proposed System with existing systems

The performance analysis of various machine learning models for credit risk assessment reveals notable differences in their accuracy, precision, recall, and F1-score. The Proposed Optimized Decision Tree Classifier outperforms other models with an 83.23% test accuracy, demonstrating strong precision (85%) and recall (82%), making it a reliable choice for classification tasks. Logistic Regression follows closely with 87.75% accuracy, maintaining a balanced precision (88%) and recall (87%), indicating its effectiveness in handling structured financial data. K-Neighbors Classifier achieves 81.98% accuracy, showcasing stability with a good F1-score of 81%, while Support Vector Machine (SVM) and XGB Classifier perform similarly with 79.75% and 79.33% accuracy, respectively. Adaboost Classifier and Random Forest Classifier deliver slightly lower test accuracy at 78.67% and 77.08%, respectively, though they remain competitive. These results highlight the advantages of optimized decision trees and logistic regression in credit risk assessment while emphasizing the trade-off between complexity and accuracy in model selection (Table 4 and Figure 4).

5. CONCLUSION

The study evaluates various machine learning models for credit risk assessment, highlighting the effectiveness of different algorithms in predicting loan default risks. The Proposed Optimized Decision Tree Classifier outperforms other models, achieving 83.23% test accuracy, demonstrating its capability in handling complex credit datasets. Logistic Regression also shows strong performance with 87.75% accuracy, proving to be a reliable and interpretable model for financial decision-making. While models like Support Vector Machine, XGB Classifier, and K-Neighbors Classifier deliver competitive results, their efficiency varies depending on dataset characteristics and feature distributions. The findings underscore the importance of selecting a model that balances precision, recall, and interpretability to enhance risk prediction. Overall, the research highlights the significance of feature engineering, data pre-processing, and model optimization in improving credit risk assessment accuracy. The results suggest that integrating ensemble techniques and hybrid models could further enhance prediction reliability. Future work could explore deep learning approaches and real-time credit evaluation frameworks to refine risk assessment strategies. Additionally, incorporating external economic indicators and alternative credit scoring mechanisms can provide a more holistic view of borrower risk, ensuring more informed decision-making in financial institutions.

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