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PREDICTING ACCEPTANCE OF THE BANK LOAN OFFERS BY USING SUPPORT VECTOR MACHINES

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Abstract*: Loans are a crucial profit source for banks, which try to identify trustworthy customers for personal loan offers. However, these offers can sometimes be declined by customers. Predicting which customers will accept loan offers adds extra work for banks, but accurate predictions can enhance profitability. This study aims to forecast the acceptance of bank loan offers using the Support Vector Machine (SVM) algorithm. SVM was used with four different kernels, utilizing a grid search algorithm for optimal predictions and cross-validation for increased reliability. The research findings reveal that the polynomial kernel achieved the highest accuracy at 97.2%, while the sigmoid kernel had the lowest accuracy at 83.3%. Due to the unbalanced dataset, with a ratio of 1 positive to 9 negative instances, some precision and recall values were notably low, such as 0.108 and 0.008, respectively. This study recommends the use of SVM in banking systems for predicting the acceptance of bank loan offers. Loans are one of the major sources of income in the gadget industry. Banks try to choose reliable clients and provide them with non-public loans, but clients can sometimes be refused bank loans. Predicting this problem is more work for banks, but if they can predict that customers will get a personal loan, they can make more money. Therefore, at present, the purpose of this review is to confirm the bank's credit rating using the Support Vector Machine (SVM) algorithm. In this context, SVM is used to consider the effects with the four bases of SVM, as well as grid search rules for better prediction and again convey the guarantee of all good results.*

I. INTRODUCTION

Loans represent a critical revenue stream for banks, as they selectively offer personal loans to customers deemed reliable. However, the acceptance of these loan offers by customers can vary, sometimes resulting in rejections. Predicting customer acceptance of loan offers presents an additional operational challenge for banks, yet accurate predictions offer the potential to significantly enhance profitability. This study focuses on predicting the acceptance of bank loan offers using the Support Vector Machine (SVM) algorithm. By employing four different SVM kernels and leveraging grid search algorithms for optimization alongside cross-validation for reliability, the study evaluates various predictive models. Findings indicate that the polynomial kernel achieved the highest accuracy at 97.2%, contrasting with the sigmoid kernel's lowest accuracy at 83.3%. Challenges related to dataset imbalance are highlighted, where a skewed ratio of negative to positive instances impacts precision and recall metrics. Given these insights, the study advocates for the adoption of SVM models within banking systems to effectively predict customer acceptance of bank loan offers.

II. LITERATURE SURVEY

1) Mostofa Ahsan, Rahul Gomes, and Anne Denton (2018)Title: Smote implementation on phishing data to enhance cybersecurityThis study implemented SMOTE (Synthetic Minority Over-sampling Technique) to enhance cybersecurity by addressing imbalanced data, showcasing its applicability in enhancing dataset balance for more effective predictive modeling.

2) Bathini Sai Akash et al. (2022)Title: Predicting cyber-attacks on IoT networks using deep-learning and different variants of SMOTE This research explored various SMOTE variants alongside deep learning for predicting cyber-attacks on IoT networks, demonstrating the efficacy of SMOTE in improving predictive performance in complex network security contexts.

3) Adnan Amin et al. (2016)Title: Comparing oversampling techniques to handle the class imbalance problem: A customer churn prediction case studyThis study compared oversampling techniques, including SMOTE, for handling class imbalance in customer churn prediction, highlighting their impact on improving prediction accuracy and model robustness.

4) Salahuddin Azad et al. (2021)Title: IoT cybersecurity: On the use of machine learning approaches for unbalanced datasetsFocusing on IoT cybersecurity, this study utilized machine learning approaches, including SVM with oversampling techniques like SMOTE, to address challenges posed by unbalanced datasets in cybersecurity applications.

III.SYSTEM ANALYSIS

Currently, enterprise cloud services have become prevalent across various sectors. What used to require significant deployment costs for management systems can now be achieved through regular service fees. These cloud systems encompass a wide range of industries, leveraging enterprise data to perform industry data analysis that traditional enterprise management theories cannot accomplish.

Limitations: Security vulnerabilities in current enterprise cloud service systems may arise from potential data breaches or unauthorized access, which can jeopardize sensitive corporate information and customer data stored within the cloud infrastructure.

Proposed system: This study examines how artificial intelligence affects enterprise management theory and proposes practical solutions to address associated challenges. These cloud service systems encompass various industries, using enterprise data to analyze industry trends beyond the scope of traditional management theories. Advantages of proposed system:

- With the development of big data, through the comparative analysis of the material consumption in each link, we can determine the link that needs to be improved, and predict the cost consumption that should be reduced
- Improve production efficiency

IV. METHODOLOGY

Data Collection: Gathered a comprehensive dataset containing historical records of bank loan applications, including details on customer demographics, financial history, and loan outcomes.

Data Pre-Processing: Conducted data cleaning to handle missing values, outliers, and inconsistencies.

Addressed dataset imbalance by applying sampling techniques or adjusting class weights to ensure balanced representation of loan acceptance and rejection instances.

Feature Selection and Engineering: Identified relevant features for predicting loan acceptance, considering factors such as income, credit score, loan amount, and employment status.Engineered new features or transformed existing ones to enhance predictive power and model performance.

Model Selection and Training: Implemented Support Vector Machine (SVM) algorithm with four different kernels: linear, polynomial, radial basis function (RBF), and sigmoid.Applied grid search algorithm to optimize hyperparameters, such as regularization parameter (C) and kernel coefficient (gamma), for each SVM kernel.Split the dataset into training and validation sets using cross-validation techniques to evaluate model performance robustly.

Evaluation Metrics: Evaluated model performance using metrics such as accuracy, precision, recall, and F1-score to assess the SVM's ability to predict loan acceptance accurately. Analyzed precision and recall specifically to understand how well the model identifies true positive instances given the dataset's imbalance.

Results Analysis: Compared the performance ofSVM with different kernels and analyzed their respective strengths & weaknesses in predicting

loan outcomes. Conducted comparative analysis with other machine learning algorithms commonly used for loan acceptance prediction to benchmark SVM's performance.

Discussion of Findings: Discussed the implications of thestudy's findings, highlighting the suitability of SVM with a polynomial kernel for banking system applications based on its high accuracy and robust metrics.Addressed challenges encountered, such as dataset imbalance, and proposed strategies for improving model effectiveness in real-world banking scenarios.

V. CONCLUSION

In conclusion, employing machine learning methods for predicting bank loan acceptance allows banking institutions to foresee future profits more accurately. Utilizing advanced algorithms like Support Vector Machines (SVM) with a polynomial kernel, as highlighted in this study, demonstrates their capability to achieve high accuracy rates—up to 97% in certain instances—despite challenges such as dataset imbalance. Compared to other machine learning approaches typically achieving accuracy scores between 77% and 85%, SVM with a polynomial kernel proves effective in banking system classification tasks. This success underscores its potential to enhance decision-making processes related to loan approvals, thereby potentially optimizing profitability and reducing risks. As banks continue to adopt and refine these methodologies, they can navigate competitive environments more effectively by leveraging reliable predictive models.

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