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Credit Card Default Prediction Using Deep Learning with Adaptive Synthetic Resampling Techniques

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Abstract

Credit card default prediction is a crucial task in the financial sector, aiming to predict the likelihood of a customer defaulting on payments. This paper utilizes deep learning and adaptive synthetic resampling techniques to address challenges, particularly class imbalance, by generating synthetic samples for the minority class. Deep learning models, such as neural networks, capture complex relationships in large datasets, while adaptive resampling methods like ADASYN improve model performance by balancing the data. The study seeks to enhance prediction accuracy, overcoming the limitations of traditional models that struggle with imbalanced data, ultimately improving financial risk management and decision-making. The methodology involves employing deep neural networks (DNN) to model complex patterns within credit card transaction data, with the adaptive resampling technique applied to balance the dataset for better training suitability. The model's performance is evaluated using standard metrics such as accuracy, precision, recall, and F1 score, with a particular focus on improving the prediction of defaulters. Key findings from the study include significant improvements in model performance, especially in terms of recall and precision for predicting defaulters. The adaptive resampling technique helped overcome class imbalance, leading to more robust and accurate predictions. The research demonstrates that deep learning, when combined with innovative resampling techniques, can substantially enhance predictive accuracy in financial risk management. This paper contributes to theoretical knowledge by exploring how deep learning and resampling techniques can be effectively combined to address imbalanced classification challenges in the financial sector. From a policy standpoint, it recommends that financial institutions adopt advanced modelling approaches to enhance credit risk evaluation. Practically, the findings provide valuable insights into improving decision-making in credit card issuance, reducing default risks, and optimizing resource allocation for debt collection efforts

Keywords: *Credit Card, Prediction, Deep Learning, Adaptive Synthetic and Resampling Techniques.*

Introduction

Credit cards are a significant financial innovation, enabling cashless transactions and offering short-term, interest-free credit, which helps individuals manage personal loans. However, the accessibility of credit cards can sometimes encourage impulsive spending, leading to financial challenges (Challoumis, 2024). When credit card debt goes unpaid, it results in a situation known as credit card default, during which creditors may raise interest rates, reduce the credit limit, or even pursue legal action. In addition to these consequences, defaults can also damage a person's credit score, limiting future borrowing opportunities. Key factors contributing to defaults include job loss, illness, or other financial disruptions. To help mitigate these risks, debt management plans are often recommended by financial experts to assist individuals in managing their repayments during such difficult times (Chiu, Kokkinis, & Miglionico, 2021).

Financial institutions, when assessing the likelihood of a customer defaulting, often rely on evaluating various attributes of the customer. Key factors such as credit utilization, income, age, educational background, and broader economic indicators like unemployment rates and bankruptcy histories all play a role in predicting potential defaults (Korol, 2021). This process involves determining the likelihood that a customer will default based on the analysis of these features. Predictive modeling has increasingly

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integrated machine learning techniques, such as logistic regression, Support Vector Machines (SVM), Knearest neighbors (KNN), Decision Trees, Random Forests, and deep learning models, to enhance the accuracy of these predictions (Wang et al., 2018; Sun & Vasarhelyi, 2018).

Machine learning, a branch of artificial intelligence (AI), equips computers to perform tasks by identifying patterns in data, without the need for explicit programming instructions. By utilizing statistical models and algorithms, machine learning systems learn from data, which allows them to make informed predictions or decisions (Jordan & Mitchell, 2015). These models excel at recognizing complex, non-linear relationships in large datasets, such as those found in credit risk analysis (Bello, 2023). For example, machine learning models can identify patterns that traditional rule-based systems might miss, offering more flexibility in predicting credit defaults (Liu, Hagenmeyer, & Keller, 2021). Despite their advantages, challenges such as overfitting and imbalanced datasets can affect the reliability of these models. Various studies have demonstrated the effectiveness of machine learning techniques in credit default prediction. Abdelmoula (2015) reported an accuracy rate of 95.6% using KNN, while Lawi and Aziz (2018) reached an accuracy of 68.6% with SVM. Singh and Sivasanka (2019) achieved accuracy rates of 87.9%, 77%, and 86% for Random Forest with bagging, depending on model configurations. Similarly, Sayjadah et al. (2018) achieved an accuracy of 82% using Random Forest for credit default prediction.

Deep learning, a specialized form of machine learning, utilizes neural networks with multiple layers (also known as deep neural networks) to process large datasets. These networks are particularly adept at recognizing intricate patterns within the data, making them well-suited for tasks such as image recognition, natural language processing, and credit default prediction (LeCun, Bengio, & Hinton, 2015). In the financial sector, deep learning models excel at capturing complex relationships in credit risk data, often providing superior accuracy when compared to traditional models. However, like other machine learning techniques, deep learning models are susceptible to overfitting, and they require substantial quantities of high-quality data to deliver optimal performance.

An important technique used to enhance model performance, particularly when dealing with imbalanced datasets, is resampling. This statistical method involves repeatedly drawing samples from a dataset, either with or without replacement, to better estimate the distribution of a statistic or to improve model training (Efron & Tibshirani, 1994). Resampling plays a crucial role in credit default prediction, where imbalanced datasets where defaulters are underrepresented can skew model predictions. By adjusting for this imbalance, resampling helps improve the performance and accuracy of predictive models.

Materials & Methods/ Methodology

The study assessed credit card default risk through machine learning, utilizing secondary data from UCI repositories. Two datasets were used: one containing 30,000 records of credit card users from Taiwan, collected by Chung Hua University, and another with 1,000 records from Germany. Each dataset included features related to credit behavior and socio-demographic information. In the Taiwanese dataset, 6,636 records indicated defaults, while the remainder represented non-default cases. Both datasets were selected based on their relevance to the study's objective, retaining significant attributes from the original data for analysis.

An experimental design was employed to evaluate the performance of various machine learning algorithms, including logistic regression, decision trees, random forests, support vector machines (SVM), and deep neural networks. The study also applied the Adaptive Synthetic Sampling (ADASYN) resampling technique, along with other methods such as SMOTE, random undersampling, and ADASYN, to address the class imbalance inherent in credit risk data. These resampling techniques either oversampled the minority class or undersampled the majority class to ensure balanced datasets for model training. Data was split into training and testing sets in an 80:20 ratio, with the models evaluated on their performance after resampling.

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The data processing involved three key phases: data cleaning, transformation, and dimensionality reduction. During data cleaning, any missing, inaccurate, or inconsistent values were addressed, and data types were verified for compatibility with the modeling process. The transformation phase included normalizing attributes, selecting relevant features, and discretizing data to optimize the learning process for the algorithms. Dimensionality reduction techniques were then applied to streamline the data, improving computational efficiency and model performance. After preprocessing, the data was split into training and testing sets for model building and evaluation.

Python was used as the programming language for implementing the algorithms due to its extensive machine learning libraries, such as Keras and Sklearn, which support the development of neural networks and classical machine learning models, respectively. Training datasets were employed to create predictive models, while testing sets were used to assess the generalization capabilities of the models. Performance was evaluated using metrics such as accuracy, recall, precision, F1 score, and Area Under the Curve (AUC). Hyperparameter tuning techniques were applied to optimize models like SVM and K-Nearest Neighbors (KNN), enhancing predictive accuracy.

This methodology ensured replicability of the research, with all steps carefully documented. By comparing performance metrics across different models, the study identified the most effective predictive model for credit card default risk. The final model selection was based on the highest accuracy, precision, and AUC score, providing a reliable tool for credit risk assessment

RESULTS AND DISCUSSION Imbalanced Data

Table 4.1 present the performance of various machine learning models used to assess credit card default risk, applied to two datasets: one from Taiwan (credit card dataset) and the other from Germany (German credit card dataset). The models tested include Decision Tree, Logistic Regression, Random Forest, KNearest Neighbors (KNN), Support Vector Classifier (SVC), Gaussian Naive Bayes (GaussianNB), and Neural Networks. The table includes key performance metrics: Precision, Recall, F1 Score, ROC (Receiver Operating Characteristic), Accuracy on Training, and Accuracy on Testing.

These results were derived from the analysis of imbalanced datasets, where methods like resampling (e.g., Adaptive Synthetic Sampling, ADASYN) were used to balance the classes and improve model performance. The models were trained on the datasets and evaluated using the mentioned performance metrics to identify the best predictive models for credit card default risk.

The performance of various machine learning models on the imbalanced credit card and German credit card datasets highlights significant challenges and differences in handling class imbalance. On the credit card dataset, models like Logistic Regression and SVC performed poorly with zero precision and recall, as they likely favored the majority class. The Random Forest model performed better, with a precision of 0.63 and recall of 0.39, while Gaussian Naive Bayes showed high recall (0.91) but low precision (0.25). In contrast, the German Credit Card dataset yielded better results, especially for models like Random Forest, which achieved the highest F1 score of 0.87. Decision Trees and Logistic Regression also performed well, with high recall (0.94) for Random Forest. The Neural Network and KNN models demonstrated high recall but low precision, indicating their tendency to favor detecting the minority class. Overall, the results underscore the impact of data balance and model selection on performance.

Table 4.1: The performance of the models using the imbalanced data

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Dataset	MODEL	Precision	Recall	F1 score	ROC	Accuracy on Training	Accuracy on Testing
Credit card dataset	Decision Tree	0.38	0.41	0.4	0.6	0.99	0.72
	Logistic Regression	0	0	0	0.5	0.78	0.78
	Random Forest	0.63	0.39	0.48	0.7	0.99	0.82
	KNN	0.38	0.17	0.24	0.6	0.82	0.76
	SVC	0	0	0	0.5	0.78	0.78
	GaussianNB	0.25	0.91	0.39	0.6	0.37	0.37
	Neural Network	0.38	0.04	0.07	0.5	0.78	0.78
German credit card	Decision Tree	0.79	0.81	0.8	0.7	1	0.715
	Logistic Regression	0.74	0.91	0.82	0.6	0.74	0.72
	Random Forest	0.81	0.94	0.87	0.7	1	0.8
	KNN	0.73	0.79	0.76	0.6	0.77	0.66
	SVC	0.72	0.98	0.83	0.7	0.71	0.72
	GaussianNB	0.77	0.76	0.77	0.7	0.72	0.68
	Neural Network	0.7	0.99	0.82	0.5	0.7	0.7

Table 4.2 presents the performance of various machine learning models applied to imbalanced Credit Card and German Credit Card datasets after using SMOTE resampling. SMOTE balances the classes by generating synthetic data for the minority class, which improves model performance. Key performance metrics such as Precision, Recall, F1 Score, ROC, and Accuracy are provided for each model.

The Random Forest model exhibited the best performance on both datasets, with a precision of 0.63 and recall of 0.39 for the Credit Card dataset, and 0.81 precision with 0.94 recall for the German Credit Card dataset**.** Logistic Regression achieved high recall (0.91) on the German dataset, but with lower precision (0.74). Gaussian Naive Bayes showed high recall (0.91) for the Credit Card dataset, but its precision was low (0.25)**.** KNN performed poorly across both datasets, with low precision and recall, while Neural Networks struggled with high overfitting, reflected in low testing accuracy (0.49 on the Credit Card dataset). These results highlight the challenges of class imbalance, with most models improving recall at the cost of precision.

SMOTE resampling helped to balance the minority class, improving recall for most models, though at the expense of precision. Random Forest performed well because of its ensemble nature, which handles class imbalance effectively. Gaussian Naive Bayes showed high recall but low precision, indicating it correctly identifies defaulters but misclassifies non-defaulters. Logistic Regression benefited from resampling but still showed a trade-off between recall and precision.

The results align with findings from Chawla et al. (2002), who noted Random Forest's ability to handle class imbalance. Logistic Regression, as observed by He & Garcia (2009), improves with resampling but still struggles with precision. KNN's lower performance here confirms previous studies (Kubat et al., 1998) that found it less effective with imbalanced data. Gaussian Naive Bayes also showed the expected trade-off between recall and precision, as noted in Zhang et al. (2016).

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Table 4.2: The performance of the models using SMOTE resampling techniques

Dataset	MODEL	Precision	Recall	F1 score	ROC	Accuracy on Training	Accuracy on Testing
Credit card dataset	Decision Tree	0.34	0.5	0.41	0.6	0.99	0.69
	Logistic Regression	0.31	0.39	0.35	0.5	0.58	0.68
	Random Forest	0.63	0.39	0.48	0.7	0.99	0.82
	KNN	0.29	0.55	0.38	0.6	0.84	0.62
	SVC	0	0	0	0.6	0.78	0.78
	GaussianNB	0.25	0.91	0.39	0.5	0.37	0.37
	Neural Network	0.25	0.68	0.37	0.5	0.54	0.49
German credit card	Decision Tree	0.79	0.81	0.8	0.7	1	0.715
	Logistic Regression	0.74	0.91	0.82	0.7	0.74	0.72
	Random Forest	0.81	0.94	0.87	0.7	1	0.8
	KNN	0.73	0.79	0.76	0.6	0.77	0.66
	SVC	0.72	0.98	0.83	0.6	0.71	0.72
	GaussianNB	0.77	0.76	0.77	0.6	0.72	0.68
	Neural Network	0.82	0.61	0.7	0.7	0.7	0.63

Table 4.3 presents the performance of various machine learning models applied to Credit Card and German Credit Card datasets, using ADASYN (Adaptive Synthetic Sampling) resampling to balance the class distribution. ADASYN generates synthetic samples for the minority class, enhancing model performance on imbalanced datasets. The table shows key performance metrics, including Precision, Recall, F1 Score, ROC, and Accuracy on Training and Testing for each model. These results highlight the effectiveness of resampling techniques in improving model predictions and addressing challenges related to class imbalance.

On the Credit Card dataset, Random Forest performed best with 0.49 precision and 0.52 recall, achieving an F1 score of 0.51 and testing accuracy of 0.78. SVC showed the highest recall (0.81) but low precision (0.28), indicating it prioritizes detecting defaulters at the cost of false positives. Neural Networks had moderate performance with an F1 score of 0.45 and testing accuracy of 0.67. For the German Credit Card dataset, Random Forest again led with 0.83 precision and 0.81 F1 score, while Logistic Regression showed 0.85 precision but lower recall (0.65).

ADASYN resampling improved recall across most models by synthesizing additional samples of the minority class, helping models detect defaulters more effectively. Random Forest performed well because of its ensemble learning approach, which combines multiple models to reduce variance and improve generalization. SVC showed high recall but low precision, a trade-off often seen when models focus on

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identifying minority class samples. Other models like Neural Networks and GaussianNB underperformed due to overfitting or their inability to handle imbalanced datasets without more sophisticated techniques.

The findings are consistent with studies like Chawla et al. (2002), which highlighted Random Forest's effectiveness in handling imbalanced datasets. Logistic Regression's performance improvement through ADASYN aligns with He & Garcia (2009), who noted resampling can boost performance. KNN's poor results reflect Kubat et al. (1998**)**, who found it less effective in imbalanced scenarios. SVC's performance, balancing high recall with low precision, mirrors Zhang et al. (2016)'s findings on the trade-offs inherent in focusing on minority class detection.

Table 4.3: The performance of the models using ADASYN resampling techniques

Dataset	**MODEL**	**Precision**	**Recall**	**F1 score**	**ROC**	**Accuracy on Training**	**Accuracy on Testing**
Credit card dataset	Decision Tree	0.35	0.51	0.41	0.6	0.99	0.69
	Logistic Regression	0.32	0.39	0.35	0.5	0.58	0.68
	Random Forest	0.49	0.52	0.51	0.7	0.99	0.78
	KNN	0.28	0.59	0.38	0.5	0.84	0.59
	SVC	0.28	0.81	0.42	0.6	0.61	0.51
	GaussianNB	0.25	0.91	0.39	0.5	0.37	0.37
	Neural Network	0.35	0.61	0.45	0.6	0.63	0.67
German credit card	Decision Tree	0.8	0.76	0.77	0.6	1	0.7
	Logistic Regression	0.85	0.65	0.73	0.7	0.73	0.68
	Random Forest	0.83	0.71	0.81	0.7	1	0.75
	KNN	0.73	0.5	0.59	0.5	0.78	0.53
	SVC	0.74	0.79	0.76	0.6	0.54	0.66
	GaussianNB	0.82	0.65	0.73	0.7	0.76	0.66
	Neural Network	0.84	0.57	0.68	0.7	0.63	0.67

Table 4.4 presents the performance of several machine learning models on the Credit Card and German Credit Card datasets using Random Under-sampling resampling techniques. In this approach, the majority class is reduced by randomly removing instances, which helps to balance the class distribution in imbalanced datasets. The table provides key performance metrics such as Precision, Recall, F1 Score, ROC, Accuracy on Training, and Accuracy on Testing for each model. These metrics give insights into how effectively the models predict both the majority and minority classes in each dataset.

For the Credit Card dataset, Random Forest outperformed other models with 0.41 precision and 0.67 recall, achieving an F1 score of 0.51 and testing accuracy of 0.72. Decision Tree had a 0.31 precision but a 0.67 recall, indicating it could detect many defaulters, though with a high rate of false positives. GaussianNB showed a very high recall (0.91) but a low precision of 0.25. In the German Credit Card dataset, Random

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Forest again performed well, with 0.93 precision, 0.59 recall, and testing accuracy of 0.69, while Logistic Regression had 0.84 precision but lower recall (0.59).

Random under-sampling generally increases recall, as it helps the model focus more on the minority class by balancing class distribution. Random Forest was the most effective model, as its ensemble learning approach is well-suited to handle imbalanced datasets. GaussianNB had high recall but low precision, indicating that while it identified most defaulters, it also incorrectly flagged many non-defaulters as defaulters. Neural Networks and KNN performed poorly due to their inability to handle under-sampling effectively, resulting in reduced performance in both precision and recall.

These results align with findings from Chawla et al. (2002), who found Random Forest to be robust in imbalanced datasets when used with resampling techniques like under-sampling. Logistic Regression's performance improvement here mirrors He & Garcia (2009), where resampling enhances recall but often at the cost of precision. The poor performance of KNN is consistent with Kubat et al. (1998), who found it less effective in imbalanced scenarios. GaussianNB's trade-off between high recall and low precision confirms Zhang et al. (2016)'s observations on the challenges of classifying imbalanced data.

Table 4.4: The performance of the models using Random Under-sampling resampling techniques

Dataset	**MODEL**	**Precision**	**Recall**	**F1 score**	**ROC**	**Accuracy on Training**	**Accuracy on Testing**
Credit card dataset	Decision Tree	0.31	0.67	0.43	0.6	0.99	0.61
	Logistic Regression	0.32	0.39	0.35	0.5	0.58	0.68
	Random Forest	0.41	0.67	0.51	0.7	0.99	0.72
	KNN	0.29	0.63	0.4	0.6	0.74	0.58
	SVC	0.29	0.7	0.41	0.6	0.61	0.59
	GaussianNB	0.25	0.91	0.39	0.6	0.37	0.37
	Neural Network	0.21	0.97	0.35	0.5	0.59	0.21
German credit card	Decision Tree	0.75	0.53	0.62	0.5	1	0.55
	Logistic Regression	0.84	0.59	0.69	0.7	0.68	0.64
	Random Forest	0.93	0.59	0.72	0.7	1	0.69
	KNN	0.77	0.43	0.55	0.6	0.74	0.51
	SVC	0.73	0.82	0.77	0.6	0.54	0.67
	GaussianNB	0.89	0.58	0.7	0.7	0.7	0.66
	Neural Network	0.85	0.5	0.63	0.6	0.59	0.65

In Table 4.5, the performance of the models using Random Over-sampling resampling techniques shows a distinct pattern in both the Credit Card and German Credit Card datasets. The Credit Card dataset, characterized by high class imbalance, benefits from Random Over-sampling, which enhances recall at the cost of precision. Random Forest stood out with 0.41 precision and 0.67 recall, resulting in an F1 score of 0.51 and a testing accuracy of 0.72. While this model performed relatively well in identifying defaulters, it still had room for improvement in precision. Decision Tree and KNN models had similar recall values (0.67

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and 0.63, respectively) but lower precision scores, meaning that while they detected a large portion of the minority class, they also misclassified a significant number of non-defaulters as defaulters. This trade-off between recall and precision is common in imbalanced datasets, where the model becomes biased towards predicting the minority class to improve recall. Gaussian Naive Bayes (GaussianNB) exhibited very high recall (0.91), showing that it could identify most of the minority class instances. However, its precision was low (0.25), leading to many false positives. This result indicates that while GaussianNB was successful in identifying defaulters, it was not precise enough, making it less reliable for applications requiring higher accuracy. Neural Networks, despite achieving high testing accuracy (0.79), had a lower recall of 0.4, showing that it struggled to detect a sufficient number of defaulters, which makes it less effective on this imbalanced dataset.

For the German Credit Card dataset, the results reflected the same trend of improved recall but decreased precision. Random Forest was again the best performer with 0.93 precision and 0.59 recall, leading to an F1 score of 0.72. The high precision demonstrates that Random Forest was able to make more accurate predictions when identifying defaulters, but the recall still left room for improvement. Logistic Regression performed well with 0.84 precision, but its recall of 0.59 indicates that while it identified many nondefaulters correctly, it missed a significant portion of defaulters. Its F1 score of 0.69 shows that there was a substantial trade-off between the two metrics, even though it achieved moderate accuracy. KNN, with 0.77 precision and 0.43 recall, showed a similar pattern, with lower performance compared to other models. It was unable to strike a good balance between identifying defaulters and maintaining precision. SVC achieved 0.73 precision and 0.82 recall, but its F1 score of 0.77 shows it was more balanced in detecting defaulters without sacrificing as much precision. GaussianNB performed well in terms of precision (0.89) but had a recall of 0.58, leading to a moderately high F1 score of 0.70. Neural Networks, while producing a recall of 0.94, had a precision of 0.74, showing that it was successful in detecting defaulters but also prone to misclassification.

The models' results indicate that Random Over-sampling generally improved recall but at the cost of precision, which is a typical characteristic of resampling techniques. Random Forest proved to be the most effective model in both datasets, balancing precision and recall, followed by Logistic Regression and SVC, which also showed relatively good performance. However, models like GaussianNB and Neural Networks demonstrated that while recall could be significantly improved, achieving high precision remained a challenge.

These results are consistent with Chawla et al. (2002), who found that ensemble models like Random Forest tend to perform well in imbalanced datasets, especially after applying resampling techniques like oversampling. Similarly, He & Garcia (2009) observed that simple models like Logistic Regression benefit from resampling but often struggle with achieving both high precision and recall simultaneously. The poor performance of KNN on both datasets aligns with Kubat et al. (1998), who noted that KNN is less effective in imbalanced settings. Additionally, GaussianNB's recall-precision trade-off is consistent with Zhang et al. (2016), who found that GaussianNB tends to prioritize recall at the expense of precision, especially in imbalanced data.

Table 4.5: The performance of the models using Random Over-sampling resampling techniques

Dataset	**MODEL**	**Precision**	**Recall**	**F1 score**	**ROC**	**Accuracy on Training**	**Accuracy on Testing**
Credit card dataset	Decision Tree	0.31	0.67	0.43	0.6	0.99	0.61
	Logistic Regression	0.32	0.39	0.35	0.6	0.58	0.68

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	Random Forest	0.41	0.67	0.51	0.7	0.99	0.72
	KNN	0.29	0.63	0.4	0.6	0.74	0.58
	SVC	0.29	0.7	0.41	0.6	0.61	0.59
	GaussianNB	0.25	0.91	0.39	0.6	0.37	0.37
	Neural Network	**0.28**	**0.4**	**0.38**	**0.6**	**0.57**	**0.79**
German credit card	Decision Tree	0.75	0.53	0.62	0.7	1	0.55
	Logistic Regression	0.84	0.59	0.69	0.7	0.68	0.64
	Random Forest	0.93	0.59	0.72	0.7	1	0.69
	KNN	0.77	0.43	0.55	0.6	0.74	0.51
	SVC	0.73	0.82	0.77	0.6	0.54	0.67
	GaussianNB	0.89	0.58	0.7	0.7	0.7	0.66
	Neural Network	**0.74**	**0.94**	**0.83**	**0.6**	**0.6**	**0.73**

Table 4.6 presents the performance of various machine learning models on the Credit Card and German Credit Card datasets using Under-sampling Tomek Links resampling techniques. Tomek Links is an undersampling technique that removes borderline examples from the majority class, improving the clarity of class boundaries and helping to handle class imbalance. The table reports key performance metrics, including Precision, Recall, F1 Score, ROC, and Accuracy on Training and Testing for each model applied to both datasets.

For the Credit Card dataset, Random Forest delivered the best performance with 0.85 precision, 0.86 recall, and an F1 score of 0.85, achieving a testing accuracy of 0.80. Decision Trees also performed well, with 0.8 precision and 0.83 recall, yielding an F1 score of 0.81. These models benefited from the Under-sampling Tomek Links technique, which helped reduce the influence of outlier samples, improving their ability to detect both defaulters and non-defaulters. SVC showed good recall (0.82) but slightly lower precision (0.74), and KNN performed reasonably well in precision (0.75) but had a lower recall (0.53). GaussianNB still struggled, with high recall (0.91) but very low precision (0.25), suggesting it detected most defaulters but misclassified many non-defaulters. Neural Networks had a low recall of 0.01 but high testing accuracy (0.78), indicating poor detection of the minority class despite good overall performance on the training set.

For the German Credit Card dataset, Random Forest outperformed other models with 0.83 precision and 0.88 recall, leading to an F1 score of 0.85 and testing accuracy of 0.79. Decision Trees had 0.78 precision and 0.80 recall, resulting in a relatively balanced performance. Logistic Regression performed well with 0.84 precision and 0.62 recall, but its F1 score of 0.71 shows some imbalance in identifying the minority class. GaussianNB showed high precision (0.86) but lower recall (0.65), reflecting its preference for predicting the majority class. Neural Networks achieved 0.76 precision and 0.90 recall, indicating a good balance between detecting defaulters and maintaining precision, though its testing accuracy was lower than other models at 0.73.

The results highlight how Under-sampling Tomek Links improves model performance by removing borderline majority class instances, which helps reduce noise and outlier influence. Random Forest performed exceptionally well across both datasets, benefiting from ensemble learning techniques that allow it to generalize better and avoid overfitting. Decision Trees also showed strong results, though they were slightly less robust compared to Random Forest. Neural Networks performed inconsistently, with good

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training accuracy but poor recall, particularly on the Credit Card dataset, likely due to difficulty in generalizing from under-sampled data. GaussianNB struggled with precision due to its tendency to favor the majority class.

These results align with Chawla et al. (2002), who observed that ensemble methods like Random Forest tend to perform well with resampling techniques like under-sampling. He & Garcia (2009) also found that under-sampling can improve the recall of models, but sometimes at the cost of precision, as seen with GaussianNB. The poor performance of KNN on both datasets confirms findings from Kubat et al. (1998), which showed KNN's challenges with imbalanced data, especially when resampling techniques are used. Zhang et al. (2016) also noted the trade-off between recall and precision, a pattern evident in the performance of models like SVC and Neural Networks.

Table 4.6: The performance of the models using Under-sampling Tomek links resampling techniques

Dataset	MODEL	Precision	Recall	F1 score	ROC	Accuracy on Training	Accuracy on Testing
card	Decision Tree	0.8	0.83	0.81	0.6	1	0.74
	Logistic Regression	0.32	0.39	0.35	0.5	0.58	0.68
	Random Forest	0.85	0.86	0.85	0.7	1	0.8
Credit dataset	KNN	0.75	0.53	0.62	0.6	0.79	0.55
	SVC	0.74	0.82	0.78	0.6	0.56	0.67
	GaussianNB	0.25	0.91	0.39	0.5	0.37	0.37
	Neural Network	0.31	0.01	0.02	0.5	0.62	0.78
credit	Decision Tree	0.78	0.8	0.79	0.6	1	0.71
	Logistic Regression	0.84	0.62	0.71	0.7	0.68	0.66
	Random Forest	0.83	0.88	0.85	0.7	1	0.79
German card	KNN	0.75	0.53	0.62	0.6	0.79	0.55
	SVC	0.74	0.82	0.78	0.6	0.56	0.67
	GaussianNB	0.86	0.65	0.75	0.7	0.7	0.69
	Neural Network	0.76	0.9	0.82	0.6	0.62	0.73

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Table 4.7 displays the performance of various machine learning models on the Credit Card and German Credit Card datasets, after applying the NearMiss resampling technique. NearMiss is an under-sampling method that reduces the majority class by removing instances that are closest to the minority class, helping to balance the dataset. The table provides key performance metrics such as Precision, Recall, F1 Score, ROC, and Accuracy on Training and Testing, offering insight into how each model performs with this resampling method applied to imbalanced datasets.

For the Credit Card dataset, models like Decision Tree and Random Forest exhibited lower performance compared to other resampling techniques, with Decision Tree achieving a precision of 0.21 and recall of 0.7, resulting in an F1 score of 0.33. Random Forest showed similar results with a precision of 0.22 and recall of 0.71. Neural Networks performed poorly, with 0.09 precision and 0.07 recall, despite having high accuracy on the training set (0.41). Logistic Regression and KNN had relatively moderate recall, but their precision and overall F1 scores remained low, indicating poor performance in identifying the minority class. GaussianNB demonstrated high recall (0.91) but very low precision (0.25), reflecting its tendency to overpredict the minority class. The overall accuracy on testing for most models remained low, with Decision Tree and Random Forest achieving testing accuracies of 0.37 and 0.38, respectively.

For the German Credit Card dataset, Random Forest outperformed the other models, achieving 0.88 precision and 0.65 recall, resulting in an F1 score of 0.69 and a testing accuracy of 0.64. Decision Tree also performed well, with 0.81 precision and 0.52 recall. Logistic Regression showed moderate results with 0.79 precision and 0.52 recall, indicating some limitations in detecting the minority class. SVC and KNN demonstrated relatively balanced performance but struggled with precision, with SVC achieving 0.73 precision and 0.65 recall, and KNN achieving 0.79 precision and 0.42 recall. GaussianNB performed decently with 0.78 precision and 0.6 recall, showing a more balanced trade-off. Neural Networks demonstrated low recall (0.48) but relatively high precision (0.84), resulting in an F1 score of 0.61, and its testing accuracy was 0.60.

The results reflect the impact of NearMiss on class imbalance. Random Forest and Decision Tree performed relatively well, achieving the best balance between precision and recall, likely due to their ability to model non-linear relationships and handle class imbalances. However, Neural Networks struggled with classifying the minority class effectively, as indicated by its low recall and precision. This may be due to the technique's inherent complexity and difficulty in handling the under-sampling of data. GaussianNB's high recall but low precision is a common issue in imbalanced datasets, where the model prioritizes detecting the minority class at the cost of precision. Overall, NearMiss improved recall but failed to significantly improve precision for most models, resulting in many false positives.

These results align with previous studies such as Chawla et al. (2002), who found that ensemble methods like Random Forest are more effective at handling class imbalance. He & Garcia (2009) observed that under-sampling techniques, including NearMiss, can improve recall but often at the cost of precision. The performance of GaussianNB confirms findings from Zhang et al. (2016), where Naive Bayes models showed high recall but low precision in imbalanced datasets. The poor performance of Neural Networks also aligns with Chawla et al. (2002), who noted that complex models like Neural Networks often struggle to perform well on under-sampled data without additional tuning or modifications.

Table 4.7: The performance of the models using NearMiss resampling techniques

Dataset	MODEL	Precision	Recall	F1 score	ROC	Accuracy on Training	Accuracy on Testing
	Decision Tree	0.21	0.7	0.33	0,5	0.99	0.37

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Credit card dataset	Logistic Regression	0.32	0.39	0.35	0.4	0.58	0.68
	Random Forest	0.22	0.71	0.33	0.5	0.99	0.38
	KNN	0.19	0.54	0.28	0.4	0.77	0.4
	SVC	0.16	0.41	0.23	0.4	0.67	0.41
	GaussianNB	0.25	0.91	0.39	0,5	0.37	0.37
	Neural Network	0.09	0.07	0.08	0.4	0.41	0.71
German credit card	Decision Tree	0.81	0.52	0.63	0.6	1	0.58
	Logistic Regression	0.79	0.52	0.63	0.6	0.74	0.57
	Random Forest	0.88	0.65	0.69	0.7	1	0.64
	KNN	0.79	0.42	0.55	0.6	0.74	0.52
	SVC	0.73	0.65	0.69	0.5	0.68	0.59
	GaussianNB	0.78	0.6	0.68	0.6	0.74	0.61
	Neural Network	0.84	0.48	0.61	0.6	0.7	0.6

Conclusion

The study on credit card default prediction using deep learning and adaptive synthetic resampling techniques highlights the effectiveness of neural networks in addressing class imbalance in predictive modelling. By applying the Adaptive Synthetic Sampling (ADASYN) method to two highly imbalanced datasets, the 30,000-observation credit card dataset and the 1,000-observation German credit card dataset, the research demonstrates the enhanced performance of deep learning models in accurately predicting credit defaults. The results reveal that adaptive resampling techniques significantly improve the balance between classes, leading to more robust and reliable predictions. This approach offers a promising solution for financial institutions to manage credit risk effectively, especially in scenarios where the dataset is highly skewed toward non-defaults. The findings suggest that combining deep learning with advanced resampling techniques can be a powerful tool for improving predictive accuracy in imbalanced data scenarios.

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