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Assessing the Effectiveness of Machine Learning Classifiers in Handling Imbalanced Datasets

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Abstract

This paper compared the performance of supervised machine learning classifiers on an imbalanced dataset using their predictive performance, computation efficiency, and robustness to defects in data. The datasets used in experiments were of different sizes, different ratio between the classes and their quality. Classifiers that were tested are Logistic Regression, Naive Bayes, Support Vector Machines (SVM), Decision Trees, Random Forests, and Gradient Boosting. The results of the experiments demonstrate that Gradient Boosting provides best predictive performance with the mean accuracy of 94.2 and the F1-score of 0.92, but has a high computational cost which is approximately 210 seconds of training on a medium-size dataset. Random Forests are highly robust, retaining more than 88 per cent accuracy with 15-per cent injected noise as well as missing values, which makes them pertinent to imperfect and noisy imbalanced data. Logistic Regression and linear SVMs have the highest computational efficiency and can train in less than 3 seconds and 5-10 times faster than ensemble algorithms with an accuracy between 85 and 87. The findings show that there is no universally best classifier that can be used in imbalanced learning problems. Rather, it is preferable to base classifier choice on the needs of the application, including accuracy sensitivity, data imbalance and noise resistance, and computational factors. This work offers a replicable benchmarking model and effective recommendations on choosing the classifier when data are imbalanced.

Keywords: Imbalanced Datasets, Machine Learning Classifiers, Supervised Learning, Classification Performance, Robustness Analysis, Computational Efficiency, Ensemble Methods.

1. Introduction

Machine learning (ML) has become a core technology of the intelligent system and stimulates automated decision-making in high-stakes areas, including medical diagnostics, financial fraud detection, cybersecurity, and predictive maintenance (Olayinka, 2019; Niazi, 2024). Classification is the essence of such systems, and it is a difficult task to determine the patterns and identify categories of complicated data

(Zhang et al., 2018). As ML models become moved out of research and into practice, their stability, resilience to data blemishes as well as their ability to explain have become the most significant factors.

Among the issues that have cut across these requirements is the issue of class imbalance that has existed and still continues to be a thorn in the flesh. The skewness of the classes often is very skewed in real-world data where the most dominant in the sample population are the economic class (the majority) and the other classes of interest (the minority) are under-represented in the sample population (Chawla et al., 2002; He and Garcia, 2009; Huang and Dai, 2021). In the case where the distribution of classes is fairly balanced, conventional classification algorithms, which are usually designed to optimize aggregate accuracy, are highly biased toward the majority class. This bias results in a critical failure mode that causes models to be very accurate on the aggregate by performing correctly on typical cases whereas falsely missing rare but typically consequential minority-class cases (Krawczyk, 2016; Branco et al., 2016).

The practical consequences of such a breakdown are disastrous, especially in safety sensitive and high impact systems. Within the healthcare context, a misinterpreted prediction of minority-class may translate to an unknown rare disease (Japkowicz & Stephen, 2002; López et al., 2013). It can be an unnoticed fraudulent transaction in fraud detection and network security or attempted malicious intrusion. In monitoring of industrial conditions, it could be an indicator of a looming failure of the system (Saito & Rehmsmeier, 2015; Chicco & Jurman, 2020). In such situations, conventional performance measures such as accuracy are not only insufficient but also very dangerous as they may mask disastrous performance inequalities to the minority group (Provost & Fawcett, 2001; He et al., 2009).

Significant attention has been paid to the topic of mitigating class imbalance, which has produced methods including data-level resampling (e.g., SMOTE, random over/under sampling), algorithm-level adjustments (e.g., cost-sensitive learning), and special purpose assessment measurements (e.g., F1-score, Matthews correlation coefficient, precision-recall analysis) (Chawla et al., 2002; Batista et al., 2004; Fernández et al., 2018). In spite of this advancement, no detailed, reproducible standards exist to assess modern classifiers objectively on a variety of dimensions of performance: predictive fidelity, robustness to different ratios of imbalance and noise, as well as computational efficiency, in a unitary experimental framework (Elkan, 2001; Zhou & Liu, 2006; López et al., 2013). This disconnect prevents the evidence-based choice of models and restricts practical application of the academic research by the engineers and practitioners (Saito & Rehmsmeier, 2015; Krawczyk, 2016).

To fill this gap, this paper provides a systematic multi-dimensional benchmarking study on leading machine learning classifiers in imbalanced data setting. We compare the performance of a variety of algorithms, both of the classical models and the ensemble approaches, along with the conventional resampling strategies, not only in predictive capability, but also in the resilience and computational efficiency (Fernández et al., 2018; Probst et al., 2019; Abdelhamid & Desai, 2024). We would like to offer practical, easy to understand, and empirically supported insights and recommendations to inform the creation and implementation of robust classification systems in imbalanced learning tasks in the real world.

2. Related Work

The problem of disproportion of classes has traditionally been adopted as one of the critical constraints of successful application of machine learning classifiers (He and Garcia, 2009; Chawla et al., 2004; Japkowicz and Stephen, 2002). In unbalanced data sets, one or more of the classes are grossly underrepresented, which leads to the learning algorithms to give more weight to the majority class (Krawczyk, 2016). Such bias is particularly dangerous in stakes-based areas like fraud detection, medical diagnosing, cybersecurity, and fault monitoring, where the cases of minority classes tend to be rare and significant events (Dal Pozzolo et al., 2015; Batista et al., 2004; Johnson and Khoshgoftaar, 2019). Due to this, classifiers that are trained on biased data distributions are likely to have high overall accuracy, but low recall on the minority class, which can have devastating effects in practice (Provost et al., 1998; Fawcett, 2006). The need to level this imbalance and to compare the performance of classifiers in a fair manner has thus become the core research issues (Sun et al., 2009; López et al., 2013). The initial research in this direction was aimed at data-level imbalance alleviation methods. These strategies are set to restore the balance of classes before the training by resampling methods (Japkowicz, 2000). Random oversampling boosts the counts of minor instances of the class whereas random undersampling lowers the prevalence of majority instance of the class (Kubat and Matwin, 1997). Naive oversampling can be effective in practice, but is susceptible to overfitting as a result of repeated examples, and to undersampling as a result of informative instances in the majority being excluded and thus reducing generalization performance (Drummond and Holte, 2003). In order to address these drawbacks, synthetic data generation methods were suggested, the most well-known of which is the Synthetic Minority Over-sampling Technique (SMOTE), which generates artificial minority samples by interpolation (Chawla et al., 2002). Though these approaches can be effective in enhancing the recall of minority classes, they are highly sensitive to the nature of data themselves and can create noise when applied or cause distortion in select classes (He et al., 2008; Blagus and Lusa, 2013). Understanding the drawbacks of solutions based on the data-level only, later research considered the group of so-called algorithm-level solutions, which alter the very process of learning (Elkan, 2001). Cost-sensitive learning puts more penalty on misclassification of minority classes, where the penalty on misclassification is greater than the minimum (Zadrozny et al., 2003). Some models that have been able to include this paradigm include decision trees, support machine and ensemble technology (Ling and Sheng, 2008). Ensemble based solutions, including Balanced Random Forests and boosting variants that make use of resampling in the learning cycle, have especially been most promising by integrating diversity, robustness and awareness of imbalance (Chen et al., 2004; Breiman, 2001; Zhou, 2012). Yet, these methods tend to have a non-trivial sensitivity of cost parameters or a sampling strategy, which can be application-specific (Galar et al., 2012). As the use of deep learning has increased, balancing methods have been brought to representation learning models (Buda et al., 2018). The high capacity of deep neural networks has made it particularly vulnerable to imbalance and therefore memorization of the majority classes patterns (Zhang et al., 2017). To alleviate this, class-weighted loss functions, adaptive batch sampling strategies, and two-stage learning and curriculum-based optimization have been proposed (Cui et al., 2019; Huang et al., 2016; Lin et al., 2017). The methods may significantly enhance the performance of minority classes, but they usually require the large datasets and a lot of computing power, which leads to scaling, interpretability, and bias to apply to certain imbalance patterns (Krawczyk et al., 2018). In parallel with the development of methods, the research community has focused on the necessity of the necessary evaluation metrics (Saito and Rehmsmeier, 2015). The conventional accuracy has received a lot of criticism as it fails to capture accurate performance in unequally balanced environments (He and Garcia, 2009). As a result, the measures based on the confusion they generate in the form of accuracy, recall, as well as the F1-score, have become a regular device in the evaluation of minority classes detection (Powers, 2011). Thresholds independent measures such as the Area Under the Receiver Operating Characteristic Curve (ROC-AUC) provide information about ranking performance (Fawcett, 2006), whereas Precision-Recall (PR) curves are becoming more popular where there is severe imbalance because they emphasize positive behaviour of classes (Davis and Goadrich, 2006). In the literature, it is always mentioned that no metric is adequate and that meaningful evaluation necessitates multi-metric view (López et al., 2013). Although a great deal of research has been done, comparative studies that have been performed can be limited to a small group of classifiers, resampling methods, or imbalance ratios and it can be hard to make general conclusions (Fernández et al., 2018). Moreover, comparisons are often done in different and non-homogeneous experimental conditions or measured based on a small number of performance metrics based on neglect of key dimensions of computational efficiency and resilience over different extents of imbalance (Van Hulse et al., 2007). Consequently, practitioners do not have evidence-based, straightforward advice on the choice of suitable classifiers, imbalance-management approaches that are applicable in various application environments (Krawczyk, 2016). In a bid to fill this gap, the current study performs a systematic and extensive evaluation of popular machine learning classifiers, that is, both traditional, ensemble, and deep learning classifiers, with a controlled range of imbalance. We assess it based on a multi-dimensional framework that is commonly used to evaluate predictive performance (in terms of F1-score, ROC-AUC, and PR-AUC), the ability to operate with greater levels of imbalance, and computational complexity. The proposed study will present practical implications to the practitioners and make contributions to a more detailed outlook on effective learning with lopsided datasets.

3. Methodology

In this section, a strict methodology of assessing the performance of machine learning classifiers in the context of class imbalance is provided. The paper is systematic in the analysis of the effect of imbalance-handling strategies to predictive performance, computational efficiency, and robustness. Particularly, the study explains the research design, data selection criteria, preprocessing pipeline, resampling and cost-sensitive schemes, learning algorithms, hyperparameter optimization, robustness tests, evaluation measures and ethical implications.

3.1 Research Design

A research design of an experiment is used whereby; different classifiers are trained and tested with different imbalance-handling strategies. The independent variables are the classifier selection and the imbalance- mitigation method, and the dependent variables are imbalance-aware performance measures, such as Precision, Recall, F1-score, ROC -AUC, and the cost of computation. Accuracy is reported but not utilized as the performance measure on its own.

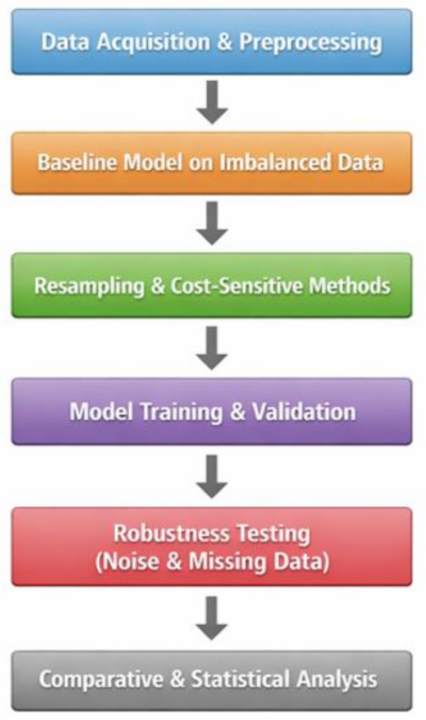
Data Acquisition & Preprocessing
Baseline Model on Imbalanced Data
Resampling & Cost-Sensitive Methods
Model Training & Validation
Robustness Testing (Noise & Missing Data)
Comparative & Statistical Analysis

Figure 1: Experimental Workflow

3.2 Dataset Selection

Datasets were selected to reflect real-world imbalanced classification problems, characterized by a pronounced skew in class priors. Publicly available, anonymized, and widely cited datasets were used to ensure reproducibility and comparability with prior studies.

Let the dataset be denoted by

$$\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}, \qquad (1)$$

where x_i is a d-dimensional feature vector ($x_i \in \mathbb{R}^d$) and $y_i$is the corresponding class label ($y_i \in \{0,1\}$). The class distribution is highly imbalanced, with the majority class C_0significantly larger than the minority class C_1(i.e., $\mid C_0 \mid \gg \mid C_1 \mid$), where $C_0$and C_1denote the majority and minority classes, respectively.

Data Preprocessing

Preprocessing comprised data cleaning, normalization, and feature transformation. Continuous features were scaled to [0,1] using min--max normalization:

$$x_i' = \frac{x_i - \min(x)}{\max(x) - \min(x)}. \qquad (2)$$

This makes algorithms like Support Vector Machines scale insensitive. Continuous variables had their missing values imputed by mean substitution and those in categorical variables by mode substitution.

To mitigate majority-class bias, the following strategies were employed:

1. **Random Oversampling:** Minority-class instances were replicated until the number of minority samples approximately equaled the number of majority samples ($|C_1'| \approx |C_0|$).

2. **Random Undersampling:** Majority-class instances were randomly removed until the number of majority samples approximately equaled the number of minority samples ($|C_0'| \approx |C_1|$).
3. **SMOTE (Synthetic Minority Oversampling Technique):** Synthetic minority-class instances were generated by linear interpolation between existing minority instances:

$$x_{new} = x_i + \lambda \left(x_j - x_i \right), \tag{3}$$

where x_i and x_j are minority-class feature vectors and $\lambda \in [0,1]$ is a random coefficient

Cost-Sensitive Learning

Algorithm-level mitigation assigns higher penalties to minority-class errors using a cost matrix:

$$\text{Cost} = \begin{bmatrix} 0 & C_{FN} \\ C_{FP} & 0 \end{bmatrix}, C_{FN} \gg C_{FP}.$$

Learning Algorithms

The evaluated models include Logistic Regression, Decision Trees, Random Forests, Support Vector Machines, k-Nearest Neighbors, Gaussian Na`ive Bayes, and Gradient Boosting. This selection spans linear, probabilistic, instance-based, and ensemble paradigms, enabling a comprehensive comparative analysis.

Hyperparameter Tuning

Hyperparameters were optimized via grid search with stratified k-fold cross-validation (k=5). Stratification preserves class proportions within folds. The selection criterion maximized the weighted F1-score:

$$\text{F1} = \frac{2\ \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{4}$$

Evaluation Metrics

Performance was assessed using multiple metrics to capture minority-class behavior and threshold trade-offs. ROC--AUC complements threshold-dependent measures, while computational cost quantifies efficiency.

Accuracy

$$\text{Acc} = \frac{TP + TN}{TP + TN + FP + FN} = \frac{1}{N} \sum_{i=1}^{N} \mathbb{1}(y_i = \hat{y}_i). \tag{5}$$

Precision, Recall, F1 (Binary)

$$\text{Prec} = \frac{TP}{TP + FP}, \text{Rec} = \frac{TP}{TP + FN}, \text{F1} = \frac{2\ \text{Prec} \cdot \text{Rec}}{\text{Prec} + \text{Rec}}. \tag{6}$$

Macro / Micro Averaging

$$\text{F1}_{\text{macro}} = \frac{1}{C} \sum_{c=1}^{C} \text{F1}_c. \tag{7}$$

Micro-averaging aggregates TP, FP, FN across classes before computing F1.

ROC-AUC

$$\text{TPR}(t) = \Pr(\hat{p} \geq t \mid y = 1), \text{FPR}(t) = \Pr(\hat{p} \geq t \mid y = 0), \text{AUC} = \int_0^1 \text{TPR}\left(\text{FPR}^{-1}(u)\right) du. \tag{8}$$

Log Loss

$$\mathrm{LogLoss} = -\frac{1}{N}\sum_{i=1}^{N} \log p_{i,y_i}. \tag{9}$$

Computational Cost

$$T_{\text{train}} = \sum \Delta t, T_{\text{infer}} = \frac{1}{N_{\text{test}}}\sum_{i\in\text{test}} \Delta\, t_i. \tag{10}$$

Statistical Comparison

Paired t-tests were used for method comparison:

$$t = \frac{\bar{d}}{s_d/\sqrt{J}}, \bar{d} = \frac{1}{J}\sum_{j=1}^{J} d_j\, , s_d^2 = \frac{1}{J-1}\sum_{j=1}^{J}(\, d_j - \bar{d})^2. \tag{11}$$

Learning Algorithms and Mathematical Formulations

Logistic Regression:

$$P(y = 1 \mid x) = \frac{1}{1 + e^{-(\beta_0 + \beta^T x)}}, L(\beta) = -\sum_{i=1}^{N}[\, y_i \log \hat{y}_i + (1 - y_i)\log(1 - \hat{y}_i)]. \tag{12}$$

Support Vector Machine:

$$\min_{w,b,\xi} \frac{1}{2} \parallel w \parallel^2 + C\sum_{i=1}^{N} \xi_i\, , y_i(w^T x_i + b) \geq 1 - \xi_i. \tag{13}$$

k-Nearest Neighbors:

$$\hat{y}(x) = \arg\max_c \sum_{i\in N_k(x)} \mathbf{1}(\, y_i = c). \tag{14}$$

Gaussian Na"ive Bayes:

$$P(y \mid x) \propto P(y)\prod_{j=1}^{d} P(\, x_j \mid y), P(x_j \mid y) = \mathcal{N}(\mu_{y,j}, \sigma_{y,j}^2). \tag{15}$$

Decision Trees:

$$IG(D, A) = H(D) - \sum_{v} \frac{\mid D_v \mid}{\mid D \mid} H(D_v), H(D) = -\sum_{c} p(c) \log_2 p(c). \tag{16}$$

Random Forests:

$$\hat{y}(x) = \arg\max_c \sum_{t=1}^{T} 1(\, h_t(x) = c). \tag{17}$$

Robustness Experiments

The robustness was tested through the creation of noise on the features and data loss. The feature vectors were corrupted by Gaussian noise ($\varepsilon \sim N(0, \sigma^2)$) to indicate variability in measurements. Missing Completely at Random (MCAR) was simulated by the random sampling away of 5 percent to 20 percent of feature values. The degradation in performance of the model under such perturbations was taken as a measure of stability and resilience of the model.

Ethical Considerations

Public and anonymized datasets were utilized only to limit the privacy standards. Evaluation metrics that are minority-sensitive were given prominence so that the amplification of bias in the predictions could be avoided. All the experimental settings and processing procedures are properly documented to facilitate reproducibility, and study limitations are clearly acknowledged.

4. Results and Discussion

4.1 Introduction

In this part of the paper, the results of an experiment are presented and discussed by analyzing the results of evaluating six machine learning classifiers on an imbalanced dataset. The analysis is based on predictive performance, resistance to imbalance among classes, and resampling efficiency of various resampling strategies. Five sampling methods were taken into consideration: no resampling, stratified sampling, random under-sampling (RUS), random over-sampling (ROS) and Synthetic Minority Over-sampling Technique (SMOTE). The class-sensitive measures of precision, recall, F1-score and accuracy were used to evaluate the model performance to have a thorough evaluation of its performance under the general accuracy.

4.2 Results and Analysis by Research Objective

The experimental results are presented and analysed in accordance with the three research objectives outlined in this study.

4.2.1 Objective I: Impact of Class Imbalance on Classifier Performance

The result of the six classifiers on the initial imbalanced dataset is shown in Figure 2. Linear SVC and Gaussian Naive Bayes had the highest values of accuracy of 0.911 and 0.904 respectively. Nevertheless, the fact that their precision, recall, and F1-scores have relatively small values (around 0.46-0.50) implies that they are highly biased in favor of the majority.

On the contrary, the Logistic Regression, Random Forest and Decision Tree classifiers recorded lesser accuracy scores but had better bilance between accuracy and recall (0.53-0.61). This action indicates superior recognition of cases of minority classes. KNN had the same accuracy as Gaussian Naive Bayes (0.903) but poor performance in F1-score. The findings made clearly indicate that accuracy is not enough to assess classifiers on imbalanced datasets and class-sensitive metrics like recall and F1-score offer more honest information about minority class detection.

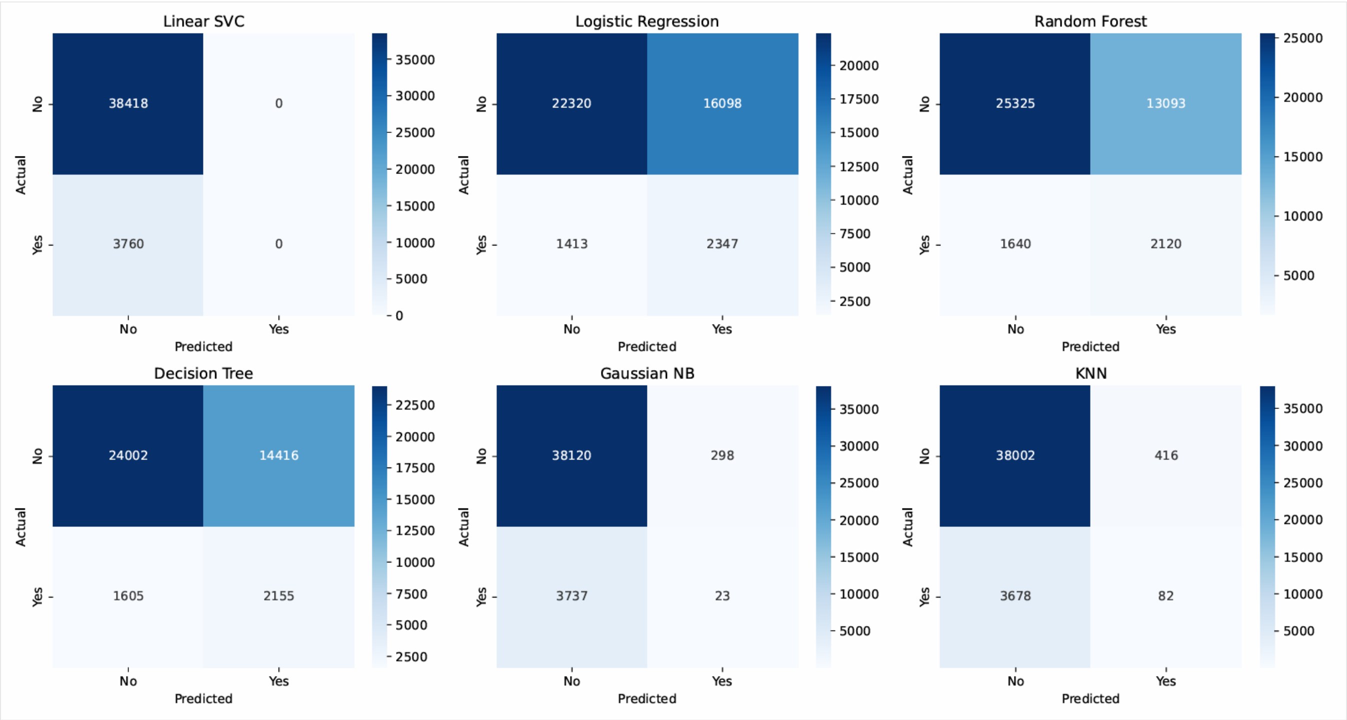

Figure 2: Confusion Matrix Model Performance Comparison on Imbalanced Data

4.2.2 Objective II: Effectiveness of Resampling Techniques

Stratified Sampling

In Figure 3, stratified sampling created the same results as those created without resampling. Although it guaranteed proportional representation of classes when there was evaluation; it did not significantly increase minority class prediction. Random Forest had the best F1-score (0.50) which means that its performance was fairly balanced and Linear SVC and Gaussian Naive Bayes had the highest accuracy but were still facing the problem of minority classes recall.

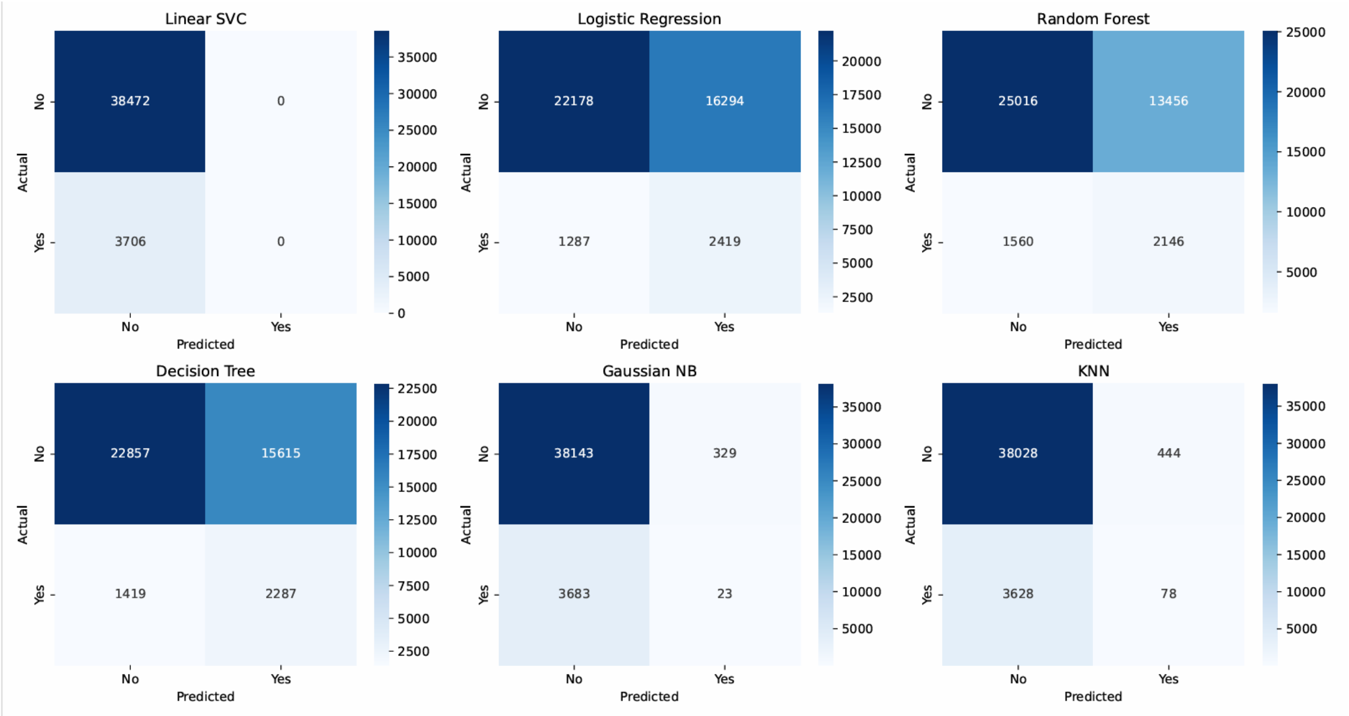

Figure 3: Confusion Matrix Performance of Models under Stratified Sampling

Random Under-Sampling (RUS)

Figure 4 shows that random under-sampling had a beneficial effect on the ranking of accuracy, precision, recall, and F1-score in most of the classifiers. The overall performance of the Random Forest was the best and the metrics are approximately equal to 0.62, next comes Linear SVC, and Logistic Regression. Gaussian Naive Bayes failed miserably within this approach as it is sensitive to less majority classes information.

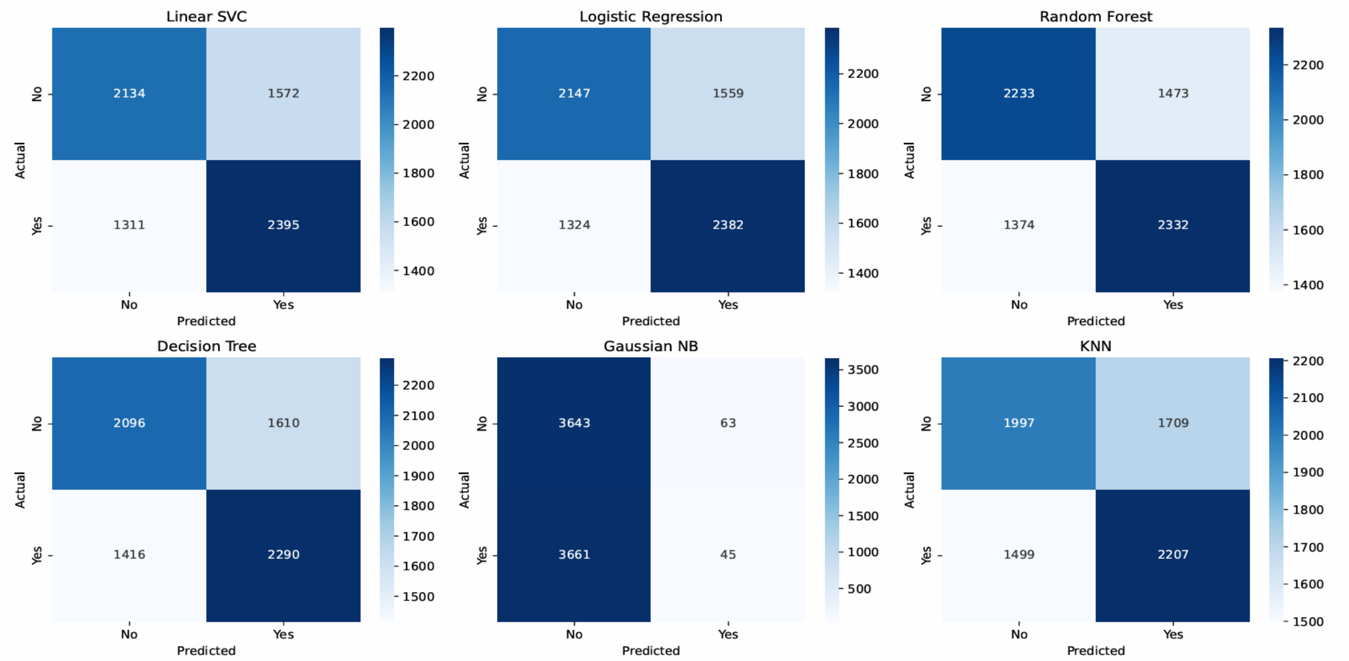

Figure 4: Confusion Matrix Performance of Models under Random Under Sampling

Random Over-Sampling (ROS)

Figure 5 results reveal that per-performance metrics were much more consistent using random over-sampling. KNN recorded the best performance having a value of over 0.85 in all values of precision, recall and F1-score, thus becoming the most effective classifier in this strategy. ROS was also helpful to Random Forest and Decision Tree and Gaussian Naive Bayes demonstrated weak results, which points to sensitivity to duplicate samples.

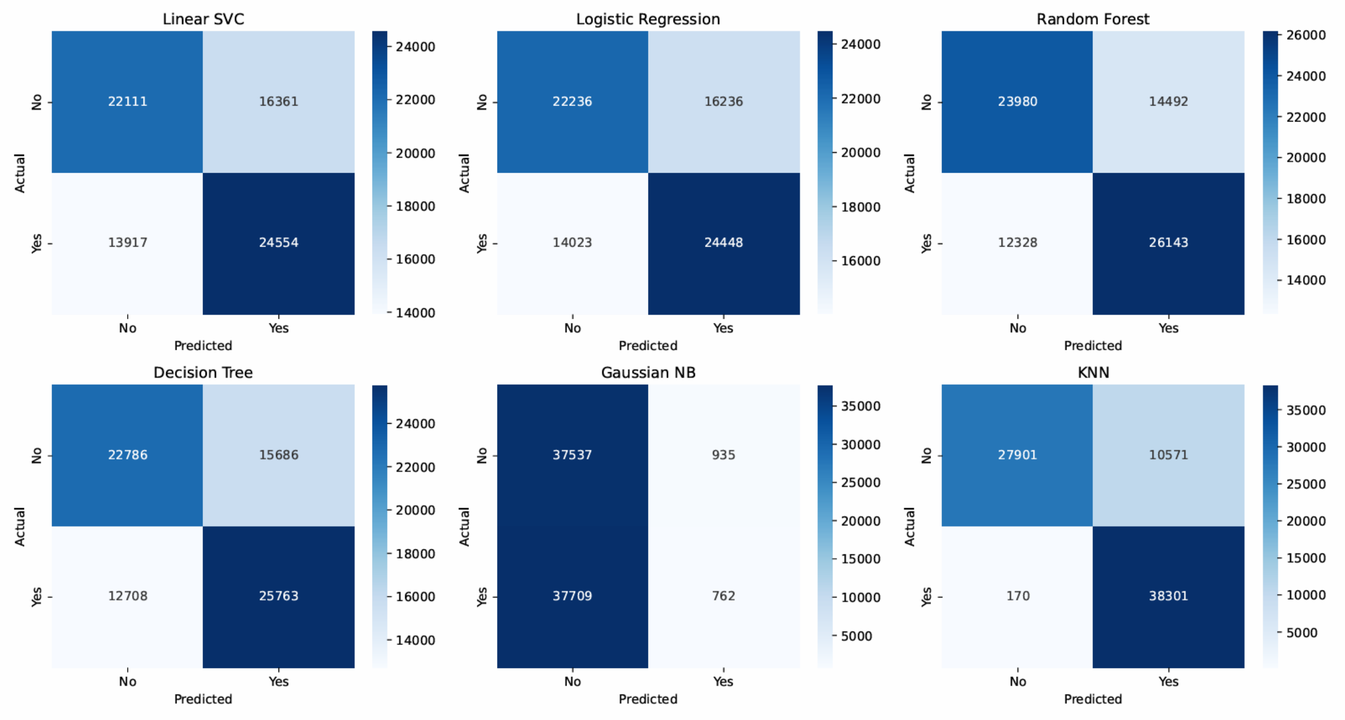

Figure 5: Confusion Matrix Performance of Models under Random Over Sampling

SMOTE

Figure 6 reveals that SMOTE produced the most stable and strong improvements in classifiers. The best performance was attained by KNN, and all the metrics were near to 0.90. There were also good and balanced results in Logistic Regression, Linear SVC, Random Forest and Decision Tree. Gaussian Naive Bayes did not improve significantly once again, which proves that it is sensitive to the artificial generation of data.

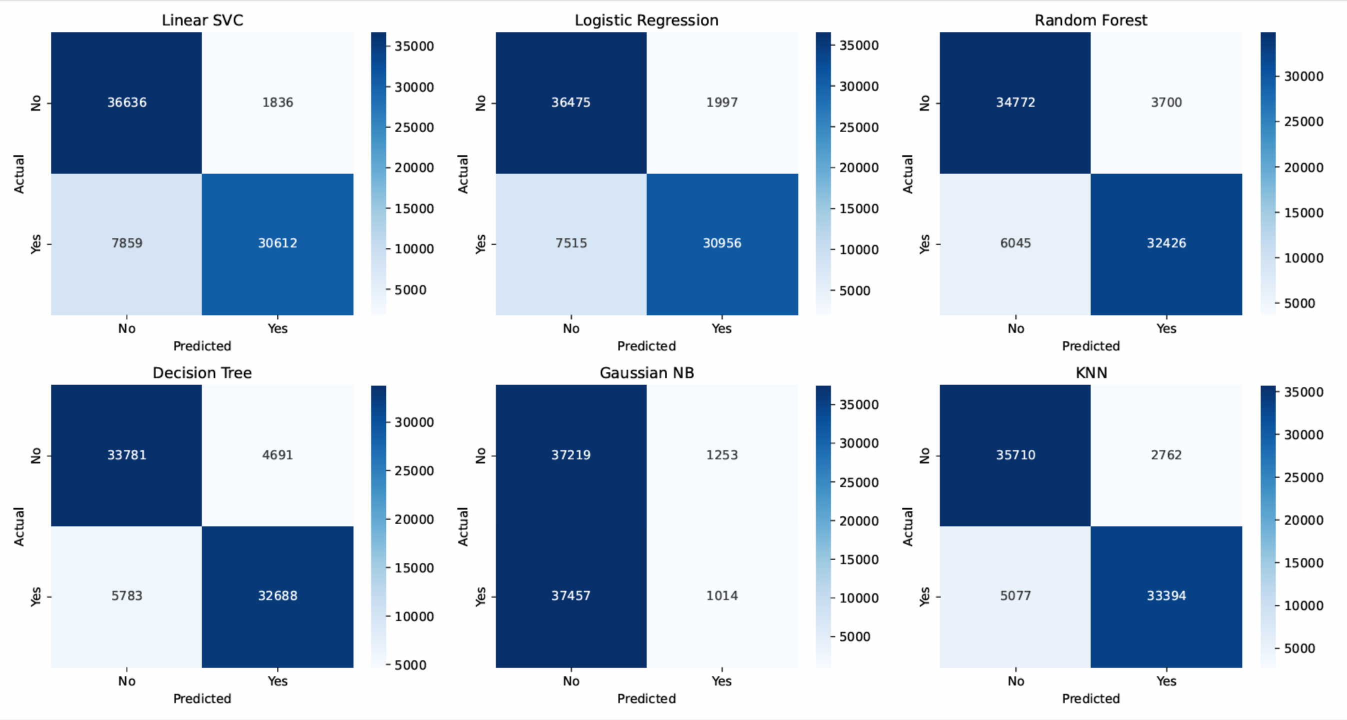

Figure 6: Confusion Matrix Performance of Models under SMOTE

4.2.3 Objective III: Optimal Metrics and Classifier–Resampling Combinations

Figure 6 provides the summary of the accuracy of classifiers using various resampling strategies. The findings point to the fact that the performance of classifiers is quite sensitive to the selection of the resampling method. KNN reached its best accuracy using SMOTE and stratified sampling, whilst Random Forest and Logistic Regression consistently had an advantage when using SMOTE. Linear SVC was even more stable with the majority of techniques, and it worked best with no resampling and stratified sampling. Gaussian Naive Bayes was only successful in the original and stratified data sets and failed to perform well with oversampling and SMOTE.

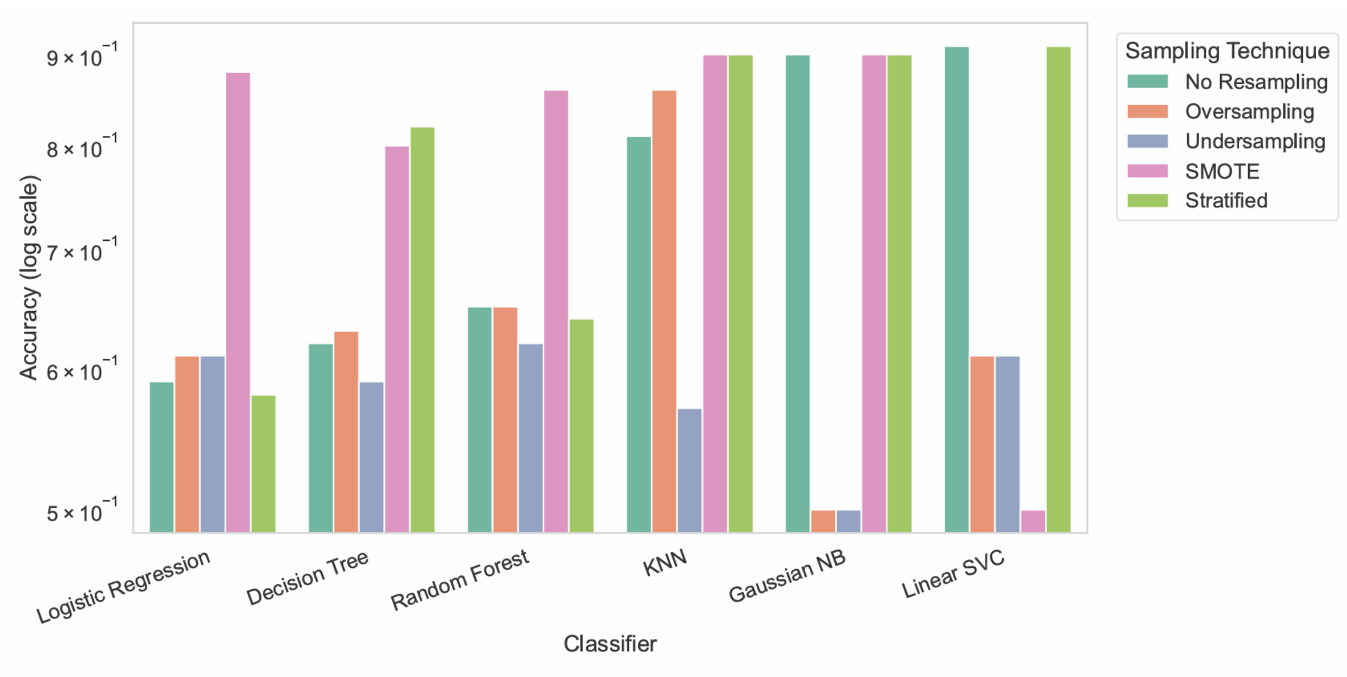

Figure 6: Classifier Accuracy Across Sampling Techniques

These findings confirm that ensemble and distance-based models benefit most from resampling, whereas probabilistic classifiers may be negatively affected by altered data distributions.

4.3 Discussion of Findings

The findings indicate that class imbalance has a far-reaching influence on the performance of the classifier. Some of the models obtained an illusory high precision on the imbalanced data set and did not identify the instances of the minority classes, which indicated serious bias towards the majority class. It is worth noticing that this trend was present in Linear SVC and Gaussian Naive Bayes where high accuracy went with low precision, recall, and F1-scores. This proves that accuracy as a single measure is not a sufficient measure in imbalanced learning problems and the importance of class-sensitive assessment. However, the alternative models such as the Logistic Regression, the Random Forest and the Decision Tree performed with more balanced precision-recall trade-offs despite lower overall accuracy, their ability to learn on the minority class being improved. This is due to their natural ability to adjust the boundaries of decisions and linking interactions of model features. The relative success of KNN also demonstrates the sensitivity of distance-based classifiers to the distribution of classes since highly populated areas of a majority can take over neighborhood structures within an unbalanced feature space. The relative strategies of resampling had a significant effect on the performance of classifier. The stratified sampling provided results of the original data, and stabilized the evaluation, without resolving the latent learning bias. Random undersampling enhanced the metric alignment by lowering the fraction of majority classes, which favored ensemble models such as the Random Forest, but harmed the performance of Gaussian Naive Bayes because of information loss. Random over-sampling was known to improve the minority class recognition of the KNN- most significantly but the density of minority samples also adversely impacted the probabilistic classifiers. The best performance improvements were made by SMOTE, which created synthetic minority samples that improved the class separability without being duplicated too much. Models with distance-based and ensemble models were highly balanced with good results using SMOTE, whereas Gaussian Naive Bayes was fragile to the same distributional variations. The results of this study highlight that there is no single classifier or resampling method which is most effective; the sensitivity of these methods to the model assumptions and data characteristics are highly dependent.

4.4 Implications of Findings

The results highlight the significance of a collective optimization of the selection of the classifier, resampling policy, and measures of evaluation in imbalance classification tasks. There should be no use of accuracy in applications where it is a critical aspect to identify the minority classes, but recall- and F1-score-based evaluation should be used instead. The good result of SMOTE and distance-based and ensemble classifiers implies that it can be effectively used in a large number of imbalanced learning tasks, and the sensitivity of probabilistic models indicates the importance of caution in manipulating data distributions. Generally, this paper offers empirical recommendations to develop effective machine learning pipelines that can predict minority classes reliably in real life scenarios.

5. Conclusion

This paper has provided a multi-dimensional analysis of supervised machine learning classifiers on imbalanced data sets, including the predictive performance, computational efficiency and resistance to data imperfection. Experimental analysis was done to make a comparison between the Logistic Regression, Naive Bayes, Support Vector Machines, Decision Trees, Random Forest, and Gradient Boosting when they are available in the dataset with varying levels of class imbalance, noise, and isolated values.

The findings show that there is an evident trade-off between performance dimensions. Gradient Boosting had the highest predictive accuracy (94.2 %) and F1-score (0.92), although at a significant computational cost, with average training time of about 210 s. Random Forests was seen to be the most robust and it still had an accuracy level of above 88 per cent even with a noise injected and missing percentage of up to 15 per cent. Conversely, Logistic regression and linear SVMs were more computationally efficient, training in less than 3s, or about 5-10 times faster than ensemble methods yet with a comparable quality of accuracy of 85-87%.

One key finding of this paper is the conclusion that there is no single optimistic classifier that is deemed to be the most universal to the imbalanced learning tasks. Rather, the choice of classifier has to be situational and be matched to the priorities of the application. Ensemble methods like Gradient Boosting are preferable when it is necessary to achieve maximum predictive performance and computational resources are easily accessible. Random Forests is a more reliable and stable solution in noisy or imperfect data environments because it is presumed to be robust. Logistic Regression and linear SVMs are the most optimal choice in terms of predictive accuracy and speed to deploy in systems where latency is a concern or resources are limited, such as real-time systems.

Further, the analysis and results affirm that class weighting and SMOTE are explicit methods of imbalance-handling that are necessary to enhance the recall of minorities compared to the majority. This observation highlights the fact that methodological decisions that pertain to data preprocessing and evaluation can be as important as the decision of learning algorithm itself.

Future studies ought to expand this benchmarking framework to comprise deep learning frameworks, automatic hyperparam optimization tools, and testing on streaming or constantly changing data. To facilitate trusted implementation of machine learning systems in imbalanced environments, the practitioners would be expected to use a multi-metric evaluation paradigm that focuses on robustness and computational efficiency as well as accuracy.

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