**Introduction**

Class imbalance problem is a common challenge in machine learning and data science, significantly affecting the development and effectiveness of predictive models. Class imbalance occurs when classes in a dataset are unevenly represented, resulting in a disparity between the majority and one or more minority classes. Most standard algorithms assume or expect balanced class distributions or equal misclassification costs. Therefore, when presented with complex imbalanced data sets, these algorithms fail to properly represent the distributive characteristics of the data and resultantly provide unfavorable accuracies across the classes of the data. (He & Garcia, 2009).

The significance of class imbalance extends across virtually all domains of application for ML, from fraud detection in banking to rare disease identification in medical diagnostics. In these contexts, the minority class often represents the event of interest, making its correct identification crucial for the model's practical utility. For example, in fraud detection, fraudulent transactions constitute a small fraction of all transactions, making them the minority class. Similarly, in medical diagnosis, the instances of a rare disease are significantly outnumbered by healthy cases or more common conditions.

Class imbalance has a negative impact on machine learning model performance in a number of ways. Firstly, traditional algorithms tend to bias towards the majority class, leading to high overall accuracy but poor recall for the minority class (Krawczyk, 2016). This overfitting to the majority class means that while the model may accurately predict common outcomes, it fails to capture the nuances and patterns specific to the rare events or conditions, which are often of greater interest (Krawczyk, 2016). Secondly, the under-representation of the minority class can lead to insufficient learning about its characteristics, resulting in a lack of generalizability and poor predictive performance on unseen data.

Class imbalance is a prevalent issue in different application domains, highlighting the crucial requirement for effective solutions. Across various industries such as finance, healthcare, social media analysis, and manufacturing, the disparity in classes poses a shared obstacle that prevents the effectiveness and equity of predictive models. Identifying rare diseases accurately in healthcare can significantly impact patient outcomes and treatment plans. Efficiently identifying fraudulent activities in the banking sector is crucial to prevent substantial financial losses among a large number of legitimate transactions.

Addressing these challenges has made the research and development of techniques to handle class imbalance crucial within the ML community. Some practitioners believe that the naturally occurring marginal class distribution should be used for learning, so that new examples will be classified using a model built from the same underlying distribution. Other practitioners believe that the training set should contain an increased percentage of minority-class examples, because otherwise the induced classifier will not classify minority-class examples well. (Weiss and Provost, 2003)

Approaches such as resampling methods, synthetic data generation, and algorithmic adjustments aim to rebalance the class distribution or modify the learning process to better account for the minority class. This work aims to not only improve model accuracy but also to promote fairness and equity in predictive results, expanding the reach and influence of ML technologies in various important fields.

Not addressing class imbalance leads to a variety of consequences that go beyond just inaccuracies in predictive modeling. When models are trained on imbalanced datasets without appropriate intervention strategies, they tend to produce predictions that are biased towards the majority class. This bias can manifest as a higher error rate for the minority class, which is frequently the class of greater interest in many real-world applications such as fraud detection, medical diagnosis, and anomaly detection in network security (Sun et al., 2011). For example, in medical diagnosis, the failure to correctly identify cases of a rare disease (the minority class) due to class imbalance can have dire consequences, potentially leading to missed diagnoses and inadequate patient care.

Also, class imbalance that isn't addressed can have big effects on society. Biased model predictions can make things even more unfair and unequal in areas like criminal justice, finance, and jobs. This is especially important when it comes to credit score systems or models that predict how police will act, because a bias toward the majority class could mean that people or groups in the minority class are treated unfairly.

Striving for a balance with suitable class imbalance solutions goes beyond enhancing model accuracy; it involves guaranteeing fairness and equity in predictions. This text is well articulated, emphasizing the importance of balanced datasets in developing fair and accurate predictive models. Highlighting the importance of fairness in applications that have a direct impact on human lives and societal structures, it is essential to have methodologies that can address class imbalance effectively.

**Application Domains**

The issue of class imbalance is widespread across numerous critical domains for the data mining community. This problem is intrinsic to some application domains. (Sun et al., 2011)

**Banking: Fraud Detection**

In the banking sector, fraud detection reflects a domain where class imbalance is a significant issue. Fraudulent transactions are infrequent in comparison to transactions that are legitimate. However, the cost associated with failing to detect these rare instances is exceedingly high, both financially and in terms of customer trust (Dal Pozzolo et al., 2015). Traditional models trained on such imbalanced datasets tend to predict most transactions as legitimate, resulting in a high rate of false negatives for fraudulent activities.

**Medical Diagnosis: Rare Disease Identification**

The medical field often grapples with class imbalance in the diagnosis of rare diseases. Datasets in these scenarios are heavily skewed towards healthy patients, with instances of rare diseases forming a small minority. This imbalance can lead to models that are proficient at identifying healthy cases but poor at detecting diseases, which is particularly dangerous in medical diagnostics where the stakes are high (Krawczyk, 2016).

**Banking: PTB Models**

In the banking industry, PTB (Propensity To Buy) models are particularly relevant due to the diverse range of products and services offered to customers, including loans, credit cards, investment products, and insurance policies. Given the vast customer base of most banks, only a subset of customers might be interested in or eligible for certain products. This scenario is a classic example of class imbalance, where the number of customers likely to buy a product (the minority class) is significantly outnumbered by those who are not (the majority class).

**Social Media: Hate Speech Detection**

The proliferation of social media platforms has ushered in challenges related to monitoring and filtering undesirable content, such as hate speech. The vast majority of content on these platforms is neutral or non-offensive, making hate speech a minority class. The risk here is twofold: models may overlook hate speech due to its rarity, or they may overfit to the minority class and incorrectly classify neutral content as offensive (Davidson et al., 2017). Addressing class imbalance through methods like focal loss or extended isolation forest can help in finely tuning the balance between sensitivity and specificity, ensuring that content moderation tools are both effective and fair.

**Network Intrusion Detection.**

Sun et al (2011) emphasizes the role of class imbalance in network intrusion detection:

*As network-based computer systems play increasingly vital roles in modern society, attacks on computer systems and computer networks grow more commonplace. Learning prediction rules from network data is an effective anomaly detection approach to automate and simplify the manual development of intrusion signatures. It is found that different types of network attacks are present, some overwhelming, others rare in the collection of network connection records.*

**Financial Management**

The class imbalance problem in financial management is just as important, and it comes with its own set of problems that affect how decisions are made, risks are assessed, and strategies are planned. Financial management includes a lot of different tasks, such as choosing investments, keeping track of stocks, figuring out credit risk, and finding financial crimes. Inequality between classes can have a big effect on all of these areas, which can make it harder to trust the predictive models that are used to make decisions about money and how to spend it. Sanz et al. (2015) tested imbalanced data classification methods in 11 financial problems including stock market prediction, credit card/loans approval application system and fraud detection (Haixiang et al., 2017).

**Manufacturing: Defect Detection**

In manufacturing, quality control processes are essential for ensuring product integrity. Here, defect detection tasks often suffer from class imbalance as the occurrence of defects is typically rare compared to non-defective items. An inability to identify these rare defects can lead to significant economic losses and harm to brand reputation. Employing class imbalance solutions, such as oversampling techniques or anomaly detection methods like isolation forest, can enhance the detection of these rare defect instances, thus ensuring higher product quality and customer satisfaction.

**Problem Statement**

Class imbalance is a significant issue in predictive modeling that makes it difficult to make fair and accurate predictions in many different areas of application. Despite the fact that this issue is widely known, there needs to be a full comparison of class imbalance solutions that take into account various levels of imbalance. This gap between the research and reality shows how important it is to carefully look into how different solutions work in different situations where classes are imbalanced. How well these solutions work may depend on aspects like the type of data, how imbalanced it is, and the specific needs of the prediction task.

This thesis aims to fill a crucial gap by conducting a thorough assessment of different class imbalance solutions across a variety of imbalance percentages.

This research has two main objectives:

**Assessment of Solutions for Class Imbalance:** Exploring a variety of class imbalance solutions such as Random Oversampling, Random Undersampling, SMOTE, EasyEnsemble, BalanceCascade, ADASyn, SMOTEBoost, Boosting SVM, LGBM Class Weights, and Focal Loss. Furthermore, in this research we address class imbalance problems as anomaly detection and explore anomaly detection algorithms like Isolation Forest, Extended Isolation Forest, Local Outlier Factor and One Class SVM. Assessing the impact of these methods on model performance across different levels of class imbalance will be the focus of this evaluation.

**Creating Practical Guidelines:** Creating practical guidelines for practitioners to address class imbalance. The guidelines are based on empirical evidence collected from evaluating the solutions mentioned, offering insights into choosing the most effective techniques depending on problem characteristics and imbalance levels.

This contribution is anticipated to have substantial implications for both academic research and practical applications, improving the accuracy, fairness, and effectiveness of machine learning models in addressing class imbalance.

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