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A Novel Ensemble Xgboost And Deep Q-Network For Pregnancy Risk Prediction On Multi Class Imbalanced Dataset

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Abstract- — Addressing imbalanced data is essential for accurate prediction. We propose a novel ensemble method of XGBoost and deep Q-learning networks (DQN) for pregnancy risk prediction. First, we train the majority class utilizing XGBoost. We subsequently utilize DQN to train the minority class into binary classifications. Finally, we use the trained models from DQN and XGBoost in ensemble learning to generate the final classification results. The XGBoost-DQN model achieves high performance with 0.9819 in precision, recall, F1-score, and accuracy, outperforming several baseline classifiers on private data from 5313 pregnant women in Indonesia and showing superior results on public datasets.

Keywords—Imbalanced dataset, Ensemble learning, XGBoost tree, Deep Q-network, Pregnancy risk.

I. INTRODUCTION

Every pregnant woman is at risk of serious, life-threatening com- plications during pregnancy. The early prediction of pregnancy risks in women enables health practitioners to provide risk-appropriate peri- natal care that saves lives [1]. Misdiagnosis might lead to patient mor- tality or high treatment expenditures. Numerous problems arise when a dataset contains a majority and a large number of minority classes, a minority and a large number of majority classes, or a large number of minority and a large number of majority classes [2]. Typically, most samples (majority class) in medical data are normal, with only a small percentage being abnormal, resulting in imbalance issues and reduced prediction accuracy. Therefore, handling an imbalanced medical dataset is a challenge.

Problems with multi-class imbalance have attracted much attention since they are significantly more complex to solve than binary imbal- ance problems because the decision border must distinguish between multiple classes. Unfortunately, the existing solutions for resolving two- class imbalanced issues may not be applicable to multi-class problems [3]. There are several challenges for classifiers when working with multi-class imbalanced datasets [4], including the skewed distribution of instances among classes, class overlap [5], and a small number of minority instances [6]. A variety of solutions have been proposed to tackle these challenges, employing both internal and external strategies. The methods can be classified into the following categories: Data-level methods, including random undersampling, SMOTE, and hybrid sam- pling techniques, seek to rebalance class distributions; however, they frequently face difficulties when applied to high-dimensional or cate- gorical data [7–10]. Algorithm-level approaches modify the learning algorithm using cost-sensitive mechanisms, threshold adjustments, or tailored loss functions to more effectively tackle class imbalance [11, 12]. Ensemble methods, such as boosting techniques like AdaBoost and RUSBoost, along with bagging strategies like BalanceCascade and EasyEnsemble [13], combine several models to enhance predictive ac- curacy for minority classes. Currently, novel deep reinforcement learning approaches are becoming increasingly popular for dealing with real-world complexity [14,15]. However, the application of deep rein- forcement learning to address imbalanced problems is still rare,
Deep Q-network (DQN) is one of the most significant achievements in deep reinforcement learning, being capable of learning successful pol icies directly from high-dimensional sensory inputs and thus replacing the Q-table in original Q-learning [16,17].

Recent advances in imbalanced data classification have gone beyond old resampling methods, bringing in smart systems that focus on the most useful and tough minority samples. Meta-learning methods, including SPE, iteratively train ensembles on difficult examples to enhance classifier robustness [18]. Hybrid generative methods, such as SMOTified-GAN, combine oversampling techniques with Generative Adversarial Networks to generate more realistic synthetic data [19]. Fed-Focal Loss, an adaptive loss function, emphasizes challenging cases during training and addresses heterogeneous data [20]. This feature renders them highly effective in complex and dispersed environments. Despite these advances, the application of deep reinforcement learning to imbalanced data remains limited. However, its potential is promising, particularly in the healthcare domain, where several methods have already demonstrated success. Jiao et al. [21] used RUSBoost to predict neonatal respiratory morbidity based on an unbalanced fetal lung, with an accuracy of 0.83 and an AUC of 0.87. Firdous and Bhardwaj [22] employed XGBoost to handle imbalanced datasets to identify pulmonary embolism and achieved an accuracy of 86 %. The accuracy was improved to 99 % by formulating an ensemble XGBoost and extreme learning machine, the IB3 tree. Alhassan et al. [23] employed deep learning stacked denoising autoencoders to predict mortality risk on imbalanced data and achieved an accuracy of 77.13 %.

XGBoost represents a powerful tree-based ensemble approach that excels at capturing complex feature interactions but can be biased to ward majority classes. DQN offers the ability to optimize for specific reward signals even with limited samples, making it well-suited for minority class detection. Unlike CNNs or LSTMs that typically require large training datasets to generalize effectively, DQN can learn from fewer samples through episodic training and experience replay. This is particularly important for medical datasets where minority classes (e.g., high-risk pregnancies) have limited examples. While deep learning models like CNNs and LSTMs provide high accuracy, they lack the interpretability of tree-based models like XGBoost. In medical applica tions, the ability to trace decision paths is valuable for clinical trust and adoption. XGBoost automatically performs feature selection and handles mixed data types without extensive preprocessing, while DQN excels at learning complex decision boundaries in high-dimensional spaces. This combination is particularly valuable for medical data with numerous heterogeneous features. The unique aspect of DQN is its ability to optimize for specific rewards. By defining rewards based on correct minority class detection, we explicitly address class imbalance beyond what traditional deep learning approaches can achieve. Thus, the inte gration of XGBoost and DQN in a unified framework brings together complementary paradigms that address the key challenges in medical risk prediction, particularly in imbalanced datasets.

This study presents an XGBoost-DQN ensemble approach to address multi-class imbalance in pregnancy datasets. This study presents the following contributions:

1. We propose a novel ensemble approach that synergistically combines XGBoost and DQN to address multi-class imbalance problems. This integration leverages the strengths of XGBoost in handling majority classes with DQN's capability to focus on minority classes through reinforcement learning.

2. We present a two-phase training methodology where majority clas ses are efficiently processed by XGBoost while minority classes are transformed into binary classification problems for specialized treatment by DQN, enabling more effective handling of the class imbalance challenge.

3. We introduce mathematical formulations that guide the ensemble integration, providing a principled approach to combining decisions from multiple models based on their specialized areas of strength.

4. We validate our method across multiple domains (medical, biolog ical, and physical) using both private and public benchmark datasets with varying degrees of class imbalance, demonstrating the approach's generalizability.

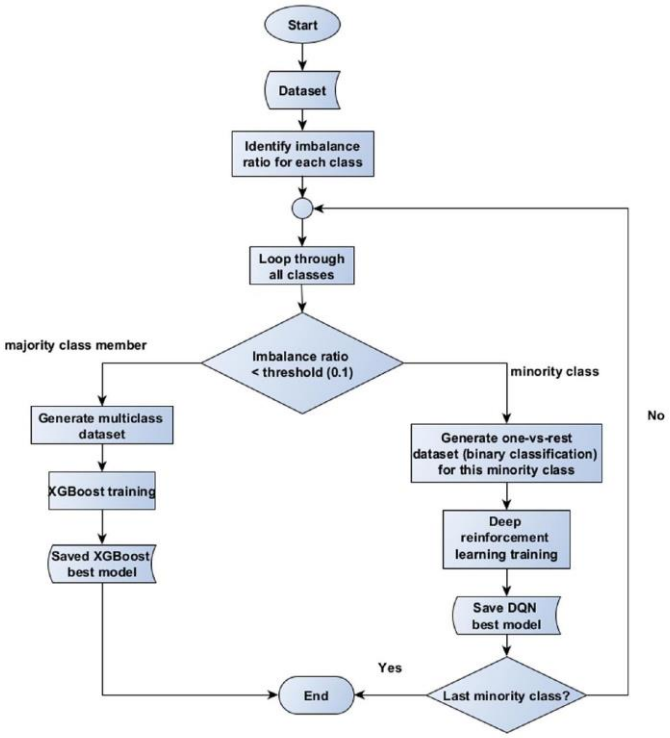
5. We provide a publicly accessible pregnancy risk dataset of 5313 re cords that can advance research in maternal health risk prediction and related machine learning applications for healthcare.

This proposed approach balances efficiency and accuracy by combining classical machine learning with deep reinforcement learning.

.II. MATERIALS AND METHOD

2.1. Data description and parameter settings

This study received ethical clearance from the Health Research Ethics Committee of Poltekkes Kemenkes Semarang, reference number No. 0294/EA/KEPK/2020. A total of 5313 pregnant women were recruited from a public health center in West Lombok Regency. The cohort study gathered data from February 2020 to February 2021 on sixteen variables: age, maternal parity, pregnancy distance, height, he moglobin, mid-upper arm circumference, HBsAg, HIV, protein, diabetes mellitus, hypertension, diastolic and systolic blood pressure, history of previous bleeding, comorbidities, and risk category. The pregnancies were categorized into four classes, based on the data: normal pregnancy (class 0), low-risk pregnancy (class



1), moderate-risk pregnancy (class 2), and high-risk pregnancy (class 3). This experimental study used 10- fold cross-validation to evaluate the performance and generalization ability of the proposed method.

2.2. Data preprocessing and feature engineering

To ensure data quality and model readiness, missing values in the dataset are imputed using appropriate strategies based on feature type. Numerical features are standardized using the formula: X where μ is the mean and σ x scaled μ = σ is the standard deviation of the feature. Categorical features are encoded using appropriate encoding scheme.

2.3. Proposed ensemble XGBoost-DQN method

Generally, the issue of class imbalance makes effective model learning difficult. Numerous classical classification methods perform poorly when dealing with class imbalance issues. Furthermore, classi fiers constructed using these techniques for such problems typically neglect the minority class to maximize the overall classification accu racy. As a result, they may be insensitive to issues of class imbalance. We propose a novel ensemble method to deal with class imbalance problems on a pregnancy risk dataset. The training process and the testing process are depicted in Figs. 1 and 2, respectively.

The training process, as shown in Fig. 1, involves multiple stages to address class imbalance. First, we compute the imbalance ratio (IR) for each class (Eq. 1) to identify minority (IR < 0.1) and majority classes. Based on the imbalance analysis, we create multiple derived datasets: (a) A multi-class dataset where minority classes are given a new com bined label (λ imb), (b) Binary datasets for each minority class, where each follows a one-vs-rest approach (the target minority class = 1, all others = 0). We then train an XGBoost model on the transformed multi-class dataset. This model focuses on differentiating between majority clas ses while treating minority classes as a single group. For each identified minority class, we train a separate DQN on the corresponding binary dataset. Each DQN specializes in detecting a specific minority class against all others: (a) The DQN architecture follows the structure in Table 2, (b) Training utilizes experience replay and target networks to stabilize learning, (c) The reward structure provides +1 for correct classifications and -1 for incorrect classifications.

All trained models (one XGBoost and multiple DQNs) are saved for the ensemble integra tion during testing.

The testing process, as shown in Fig. 2, outlines how predictions are generated on new instances using the trained models. For a given test instance with feature vector X_i, we first obtain the XGBoost prediction $YY_{xgb} = F_{xgb}(X_i)$. If XGBoost predicts a majority class ($W_{xgb} = 1$, as defined in Eq. 8), we accept this prediction directly. If XGBoost predicts a minority class ($W_{dqn} = 1$, as defined in Eq. 9), DQN verification is triggered. The instance is then passed through all relevant DQNs, which return binary predictions ($\left(YY_{dqn_j} = F_{dqn_j}(X_i)\right)$ for each minority class j) and confidence scores. The final decision is determined according to Eqs. 5-9. If no DQN confirms a minority class, assign to class 0 (normal). If one DQN confirms a minority class, assign that class. If multiple DQNs give conflicting predictions, select the class with the highest decision function value. Ensemble performance is evaluated using precision, recall, F1-score, and accuracy.

We identify the minority class and majority class by calculating the imbalanced class. Given a class set L (i.e., 0,1,2,3) and Y_i

is the class value in the i-th data, Eq. 1 is used to determine the imbalance ratio of the classes:

$$\mathrm{IR}(\lambda) = \frac{\sum_{i=1}^{m} h(\lambda, Y_i)}{\max\lambda' \in L\left(\sum_{i=1}^{m} h(\lambda', Y_i)\right)} \tag{1}$$

where h is a simple function that marks the class that is currently looking for the imbalance ratio value, as shown in Eq. 2.

$$h(\lambda, Y) = \begin{cases} 1, \lambda \notin Y_i \\ 0, \lambda \in Y_i \end{cases} \tag{2}$$

If $h(\lambda, Y)$ is less than the threshold (0.1), the member class is grouped in the imbalance set (L_{imb}); otherwise, it is grouped in the normal class. After the minority class is identified, a new dataset will be formed, which will be used for XGBoost training. If (Y_i) is identified as a member of an imbalanced class (L_{imb}), then this new dataset will be assigned a new class, namely $\lambda_{\text{imb}} = \max(L_{\text{normal}}) + 1$, as shown in Eq. 3

$$\mathrm{Yxgb}_i = \begin{cases} \lambda_{imb}, & Y_i \in L_{imb} \\ \lambda_{\text{normal}}, & Y_i \in L_{\text{normal}} \end{cases} \tag{3}$$

We then employ DQN, a deep reinforcement learning method, to train the minority class into binary classifications. For training data that is fed into DQN, it uses the one-vs-rest concept as in the imbalance ratio calculation stage. Minority classes that will be trained are assigned a value of 1 , while members of other classes are assigned a value of 0 , as shown in Eq. 4.

$$Y(\lambda_{\text{minor}})_i = \begin{cases} 1, Y_i \in \lambda_{\text{minor}} \\ 0, Y_i \in \lambda_{\text{other}} \end{cases} \tag{4}$$

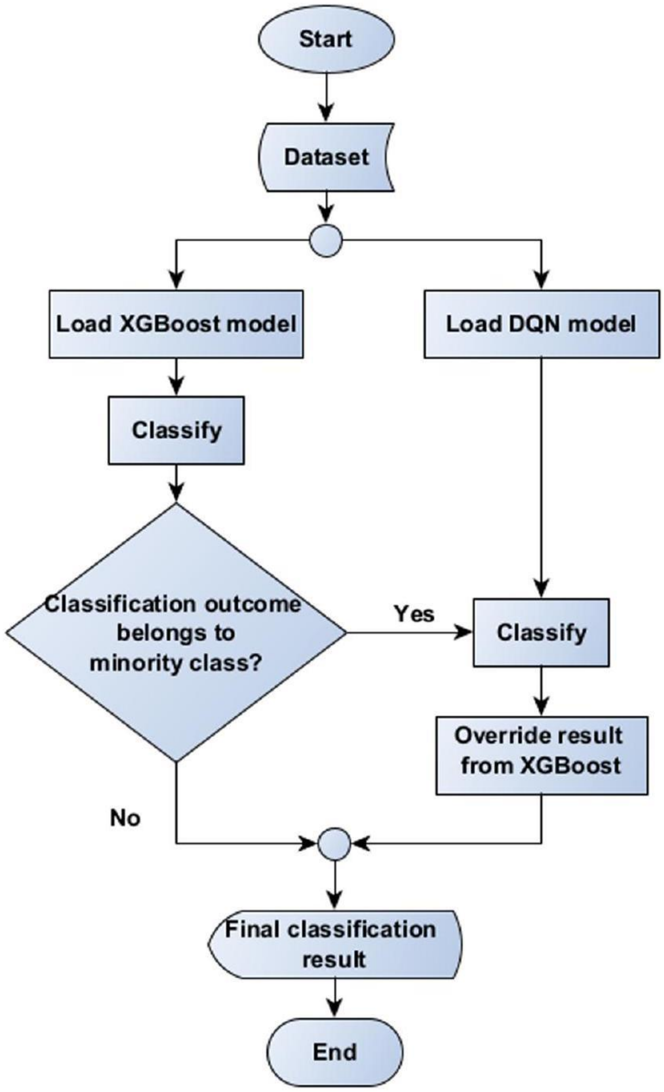
where, the following rules as shown in Eqs. 5, 6, 7, 8 apply to the XGboost result weight (W_{xgb}) and the DQN result weight (W_{dqn}):

$$YY_{xgb} = F_{xgb}(X_i) \tag{5}$$

$$YY_{dqn_i} = F_{dqn_i}(X_i) \tag{6}$$

$$W_{xgb} = \begin{cases} 0, YY_{xgb} \in \lambda_{ibm} \\ 1, \text{otherwise} \end{cases} \tag{7}$$

$$W_{dqn} = \begin{cases} 1, YY_{xgb} \notin \lambda_{ibm} \\ 0, \text{otherwise} \end{cases} \tag{8}$$



2.4. Theoretical foundation for XGBoost-DQN integration

XGBoost excels at capturing majority class patterns but may perform on minority classes due to their limited representation. Conversely, by formulating minority class detection as a binary classification problem, the DQN can focus specifically on learning the characteristics of these rare instances. The integration process works as follows:

1. Obtain the XGBoost prediction $YY_{xgb} = F_{xgb}(X_i)$, where F_{xgb} is the prediction function of the XGBoost mode.
2. If YY_{xgb} belongs to a majority class (classes 0 or 1 in our pregnancy dataset), accept this classification directly.

d. In case of conflicting DQN predictions, compare the decision function values and select the class with the higher confidence score

The decision function for conflict resolution is calculated using Eq. 10.

$$\text{decfunc}_{\text{dqn}_j}(X_i) = Q(X_i, a = 1) - Q(X_i, a = 0) \quad (10)$$

where $Q(X_i, a = 1)$ is the Q -value for taking action 1 (assigning the minority class j) and $Q(X_i, a = 0)$ is the Q -value for taking action 0 (not assigning the minority class j).

The hyperparameter configuration used for training the XGBoost model, along with the rationale for each choice, is detailed in Table 1.

3. Results and discussion

3.1. Performance of the proposed method

First, we calculate the imbalance ratio of the minority classes and majority classes. The results of the multi-class imbalance ratio show two minority classes, namely class 2 and 3, as described in Table 2. We then employ the one-vs-rest concept to treat each minority class and create a new dataset for binary classification based on this treatment for each minority class. In our case, because there are two classes whose imbal ance ratio value is below the threshold, there are two new binary clas sification problem datasets and one multiclass dataset. In one dataset, we assign the members of minority class **2** (moderate-risk pregnancy) a value of 1 (as a new class 1), while the members of the other classes (class 0, class 1, class 3) are assigned a value of 0 (as a new class 0). In another new dataset, we assign the members of minority class 3 (high- risk pregnancy) a value of 1 (as a new class 1), while the members of the other classes (class 0, class 1, class 2) are assigned a value of 0 (as a new class 0).

Table 1:XGBoost hyperparameters configuration.

Parameter	Value	Justification
learning rate	0.1	Provides balance between convergence speed and model accuracy
max depth	6	Controls tree depth to prevent overfitting while maintaining discriminative power
n estimators	1000	Sufficient iterations for convergence without overfitting
subsample	0.8	Reduces variance by using 80% of data for each tree
colsample bytree	0.8	Introduces randomization to increase model robustness
min child weight	1	Helps control over-fitting for imbalanced datasets
objective	'multi: softmax'	Appropriate for our multi-class classification problem

Table 1:Results of multi-class imbalance ratio-presents the calculated imbalance ratios for each pregnancy risk class in our dataset, highlighting the severe imbalance in moderate-risk and high-risk categories.

Class	Imbalance Ratio
Class 0 (normal)	191.603
Class 1 (low-risk pregnancy)	0.38036
Class 2 (moderate-risk pregnancy)	0.05963
Class 3 (high-risk pregnancy)	0.01123

3.3. Performance evaluation using public datasets

To further verify the effectiveness of our proposed ensemble XGBoost-DQN model, we examined it on three publicly available datasets from the UCI Machine Learning Repository, namely the ecoli dataset, yeast dataset, and glass identification dataset. The ecoli dataset is a classification of protein localization sites, comprising 336 instances with 7 features [24]. The yeast dataset is a multivariate dataset used for protein localization site prediction, comprising 1484 instances with 8 features [25]. The glass identification database is a classification of the type of glass from the USA Forensic Science Service, comprising 216 instances with nine features [26]. First, we checked the imbalance ratio of each class of the ecoli dataset, yeast dataset, and glass identification dataset, as detailed in Tables 12, 13, and 14, respectively. Tables 12, 13, and 14 show that many minority groups exhibit a low imbalance ratio (below 0.1), specifically classes 3,4,6, and 7 in Table 12; classes 5, 4, 3, 10, 9, and 2 in Table 13; and classes 3, 4, and 5 in Table 14.

Our proposed ensemble XGBoost-DQN applied on the ecoli dataset yielded the highest value compared to the other existing baseline models, with an accuracy of 0.9196 , an F1-score of 0.9198 , a precision of 0.9240 , and a recall of 0.9196 , as detailed in Table 15. Our proposed ensemble XGBoost-DQN applied on the yeast dataset yielded the highest results compared to the other existing baseline models, with an accuracy of 0.9178 , an F1-score of 0.9178 , a precision of 0.9186 , and a recall of 0.9178 , as detailed in Table 16. Our proposed ensemble XGBoost-DQN applied on the glass identification dataset yielded the highest results, compared to the other existing baseline models, with an accuracy of 0.967 , an F1-score of 0.967 , a precision of 0.968 , and a recall of 0.967.

While our ensemble method requires longer training and inference times, the significant performance improvements justify this additional computational cost for critical applications like pregnancy risk prediction.

1.1. Model generalizability and potential biases

The dataset comprises 5313 pregnant women who were recruited from a public health center located in West Lombok Regency, Indonesia. This cohort represents a distinct geographic and demographic group that may impact the distribution of risk factors. Participants were aged 18-45 years (mean: 27.6, SD: 6.3), mostly residing in rural or semiurban areas, with predominantly middle to low-income status and reliance on public healthcare. The population is primarily of Sasak ethnicity. Model biases may emerge due to local healthcare practices, disparities in access to prenatal care, cultural influences, and the presence of incomplete data patterns. To improve generalizability, it is advisable to conduct external validation utilizing diverse datasets, implement transfer learning for adaptation to target populations, perform feature importance analysis, evaluate fairness across subgroups, and ensure continual updates to the model. The proposed ensemble is designed to be dataset-agnostic; however, it can be retrained using population-specific data to reduce bias and enhance performance across diverse settings.

2. Conclusion and future work

This study presents a novel ensemble XGBoost-DQN to improve the classification performance in multi-class imbalanced problems on the pregnancy risk dataset. The proposed ensemble method consists of three steps: (1) we train the majority class using XGBoost; (2) we employ DQN to train the minority class into binary classifications; and (3) the classification results of these classifiers are combined using ensemble rules. The experiment results demonstrate that our proposed ensemble method when applied to private and public datasets outperforms seven baseline classifiers with high precision, recall, accuracy scores and F1score. The envisioned personalized health advice system leverages our established XGBoost-DQN risk prediction model and aligns with existing healthcare frameworks. The system features a recommendation engine that com- bines rule-based logic with machine learning, supports HL7 FHIR- compatible EHR integration, and provides a mobile application for pa- tients in addition to a clinician dashboard. The system integrates seamlessly into clinical workflows by automating initial risk assess- ments, continuously updating risk profiles, generating alerts for high- risk cases, and recommending care pathways tailored to specific risk factors. It automatically produces documentation for medical records. Personalization is accomplished via the analysis of risk factors, cultur- ally tailored guidance, and an assessment of accessible healthcare re- sources, with recommendations adapting as pregnancy progresses. This system is designed to enhance maternal health outcomes, especially in low-resource environments, with upcoming efforts directed towards usability and clinical validation.

Table 3

Computatioal efficiency comparison

Method	Training Time (s)	Inference Time (ms/ sample)	Memory (MB)
kNN	0.21	0.38	158
SVM	1.43	0.15	187
XGBoost	5.62	0.25	241
CNN	176.29	0.76	563
LSTM	214.87	0.94	684
DQN	285.43	1.13	427
Ensemble XGBoostDQN	296.87	1.42	668

References

[1] M. Khaskheli, S. Baloch, A.S. Baloch, Risk factors in early pregnancy complications, J. Coll. Physicians Surg. Pak. 20 (11) (2010) 744-747

[2] J.A. S'aez, B. Krawczyk, M. Wo'zniak, Analyzing the oversampling of different classes and types of examples in multi-class imbalanced datasets, Pattern. Recognit. 57 (2016) 164-178.r

[3] A. Fern²andez, V. L'opez, M. Galar, M.J. Del Jesus, F. Herrera, Analysing the classification of imbalanced data-sets with multiple classes: Binarization techniques and ad-hoc approaches, Knowl. Based. Syst. 42 (2013) 97-110.

[4] S. Garc²1a, Z.L. Zhang, A. Altalhi, S. Alshomrani, F. Herrera, Dynamic ensemble selection for multi-class imbalanced datasets, Information Sciences 445 (2018) 22-37.

[5] R. Alejo, R.M. Valdovinos, V. Garćla, J.H. Pacheco-Sanchez, A hybrid method to face class overlap and class imbalance on neural networks and multi-class scenarios, Pattern. Recognit. Lett. 34 (4) (2013) 380-388.

[6] L. Gonzalez-Abril, H. Nunez, C. Angulo, F. Velasco, GSVM: An SVM for handling imbalanced accuracy between classes inbi-classification problems, Appl. Soft. Comput. 17 (2014) 23-31.

[7] A. Fern²andez, M.J. Jesus, F. Herrera, On the 2-tuples based genetic tuning performance for fuzzy rule based classification systems in imbalanced data-sets, Information Sciences 180 (8) (2010) 1268-1291.

[8] H. Shi, Q. Gao, S. Ji, Y. Liu, A hybrid sampling method based on safe screening for imbalanced datasets with sparse structure, in: 2018 International Joint Conference on Neural Networks, 2018, pp. 1-8.

[9] C.L. Liu, P.Y. Hsieh, Model-based synthetic sampling for imbalanced data, IEEe Trans. Knowl. Data Eng. 32 (8) (2019) 1543-1556.

[10] S. He, B. Li, H. Peng, J. Xin, E. Zhang, An effective cost-sensitive XGBoost method for malicious URLs detection in imbalanced dataset, IEEe Access. 9 (2021) 9308993096.

[11] M. Phankokkruad, Cost-sensitive extreme gradient boosting for imbalanced classification of breast cancer diagnosis, in: 2020 10th IEEE International Conference on Control System, Computing and Engineering, 2020, pp. 46-51.