ASE: Anomaly Scoring Based Ensemble Learning for Imbalanced Datasets

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ABSTRACT

Nowadays, many industries have applied classification algorithms to help them solve problems in their business, like finance, medicine, manufacturing industry and so on. However, in real-life scenarios, positive examples only make up a small part of all instances and our datasets suffer from high imbalance ratio which leads to poor performance of existing classification models. To solve this problem, we come up with a bagging ensemble learning framework based on an anomaly detection scoring system. We test out that our ensemble learning model can dramatically improve performance of base estimators (e.g. Decision Tree, Multilayer perceptron, KNN) and is more efficient than other existing methods under a wide range of imbalance ratio, data scale and data dimension.

CCS CONCEPTS
• Computing methodologies → Bagging; Supervised learning by classification; Anomaly detection.

KEYWORDS
ensemble learning, imbalanced datasets, resampling, anomaly detection

1 INTRODUCTION

Classification problem is a common research area in machine learning and data mining, and have a wide range of applications in many real-world scenarios[18, 22]. With the rapid development of information technology, the scale of data has grown significantly today, and many algorithms based on mathematical statistics and traditional machine learning methods have unsatisfactory performance in the face of massive data. Confronting with skewed data, classification models tend to be inclined to the majority class and ignore the minority class as noise or merge them into the majority class. Models can only get a high accuracy on the majority class but suffer from poor performance on the minority class.

In addition to the growth of data scale, in the era of big data, we are also faced with problems such as data imbalance, high feature dimensions, and dirty data interference. In many real-world scenarios, our datasets often suffer from high imbalance ratio. In the case of imbalanced data, if the classifier judges all samples as the majority class, this can achieve extremely high accuracy, but it has no any practical value, because in the case of imbalance, people pay more attention to the classification of minority classes. For example, in medical testing, misclassify positive samples as negative samples will lead to more serious consequence than misclassifying negative samples as positive samples. In the credit evaluation, only a few customers are untrustworthy users, and the goal of the credit evaluation is to identify users who may default in the future from all the applicants. If the potential default users are not identified, the percentage of bad debt rate will increase and the companies will have a direct economic loss, so it is significant to classify the minority class correctly.

In order to overcome classification problems in imbalanced and data-overlapping scenarios, we introduce anomaly detection models[1, 7] to our ensemble Model ASE (Anomaly Scoring Based Ensemble Learning) to quantify the anomaly degree of samples. With higher scores, instances are more likely to be minority class and it is possible for us to detect the overlapping area of majority class and minority class. The proposed ASW (Anomaly Scoring Weight) affects the proportion of data splitting and we resample from different bins according to ASW. ASW depends on the contamination coefficient of anomaly detection models and we use the proposed CEW (Contamination Entropy Weight) to estimate the generalization ability of base estimators and integrate all weak learners into our ASE.

In this paper, we propose an ensemble learning framework with the scoring system based on anomaly detection algorithms. Our framework is a bagging model so it can be trained efficiently with parallel computation. When constructing each weak learner, we use an anomaly detection model to scoring all instances then we split majority samples into b bins according to the output scores. Then we construct b subsets by resampling from each bin and each subset contains different proportion of instances from different bins so that we can make our classification model to pay appropriate
attention to different bins based on their contribution to data sets’ chaos, which we introduce our concept $A_{SW}$ to quantify. Finally, we combine all weak learners with our $C_{RW}$ to construct our ensemble learning model $A_{SE}$ which can adapt to various degree of imbalance ratio, data scale and feature dimension.

In summary, this paper makes these contributions.

1) We introduce a scoring system based on anomaly detection to the resampling step of imbalance classification problems. We use this scoring system to make proposed ensemble learning framework to pay more attention to outliers and minority class so that our framework can achieve higher performance while datasets suffer from severe data skew.

2) We proposed an ensemble learning framework called $A_{SE}$ (Anomaly Scoring Based Ensemble), which is efficient enough to applied in a great number of real-life situations to handle classification tasks under high imbalance ratio.

3) We test our proposed method is much more efficient than other imbalanced classification algorithms on different real-world imbalanced tasks with various base classifiers. With our ensemble framework, we do not need any priori knowledge or pre-defined distance metrics which is inaccessible in most application scenarios.

2 RELATED WORK

Imbalance ratio (IR) is used to quantify the level of data skewing in a dataset.

$$IR = \frac{\text{number of majority class}}{\text{number of minority class}}$$

At present, there are three main techniques to deal with imbalanced data, resampling, cost-sensitive learning and ensemble learning [18].

- **Data resampling**: Resampling try to solve the problem of data imbalance by reducing datasets’ imbalance ratio or even making datasets balanced in the data level. By generating some minority class data (over-sampling) or discarding some majority class data (under-sampling), resampling methods can be divided into three categories, under-sampling, over-sampling and hybrid-sampling. Common resampling methods include RUS, ROS [3], SMOTE [8], ADASYN [21], TomekLink [41], OSS [24], etc.

Under-sampling tries to reduce imbalance ratio or construct balanced subset by discarding samples from the majority class, which may lead to information loss since we loss parts of data and is not a wise choice dealing with small scale datasets [18]. RUS is the oldest under-sampling method which discards samples randomly. Then a serious of undersampling methods derivated from Nearest Neighbor Criterion including CNN (Condensed Nearest Neighbor) [20], ENN (Edited Condensed Nearest Neighbor) [45], TomekLink [41], NM (Near Miss) [32] and NCR (Neighborhood Cleaning Rule) [25]. IHT (Instance Hardness Threshold) [39] removes the instances which have a high possibility to be misclassified by training extra classifiers and OSS (One Side Selection) [24] discards majority class by TomekLink. The idea of evolution and genetic algorithms are also applied to under-sampling like EUS [16] and GAUS [17].
In order to decrease imbalance ratio, over-sampling synthesizes new instances based on the minority class [18]. However, this usually breaks the original data distribution and when data are overlapping and highly imbalanced, this kind of method may not perform well because of overfitting. ROS (Random Over-sampling) [33] first introduced the idea of over-sampling and SMOTE (Synthetic Minority Over-sampling Technique) [8] is the most representative method of over-sampling. Based on SMOTE, variants of SMOTE spring up like Borderline-SMOTE [19], SVM-SMOTE [42]. Hybrid-sampling is a combination of under-sampling and over-sampling which tries to reduce the negative impact and take advantage of both methods. SMOTE-ENN [6], SMOTE-TomeLink [5], SMOTE-RSB [34] and SMOTE-IPF [36] are some common hybrid-sampling methods.

- **Cost-sensitive learning**: In cost-sensitive learning, a larger penalty coefficient is applied to the minority class so that the classifiers will pay more attention to the classification results of the minority class to reduce the impact of data imbalance, but it requires certain prior knowledge like a cost matrix provided by some experts in specified domains which is not often feasible in real-life situation and models have a certain probability of overfitting [18]. As the result, compared with resampling and ensemble learning, cost-sensitive learning is a less popular research area and fewer people choose using it to work our imbalanced classification problems [23]. CSSVM [40], CSNN [48] and CS-LDM [10] are widely used cost-sensitive learning methods.

- **Ensemble Learning**: Ensemble learning improves the generalization ability and accuracy of the classification models by integrating multiple weak classifiers trained by the data processed by resampling methods, but it is more easily affected by noise. The ensemble method can be divided into two categories, bagging-based ensemble learning models and boosting-based ensemble models. Common ensemble learning methods include UnderBagging [43], OverBagging [43], SMOTEBagging [43], Adaboost [14], SMOTEBoost [9], MSMOTEBoost [15], RUSBoost [37], EasyEnsemble [28], BalanceCascade [28], etc.

Bagging models can be trained parallely so they are more efficient than boosting models whose base classifiers need to be trained based on the information given by the last base classifiers. Some experts [13] have verified that bagging methods’ performance doesn’t fall behind boosting methods while cost less time in training so these methods are widely applied in practical application. Resampling bagging algorithms include OverBagging [43], UnderBagging [43] and SMOTEBagging [43], etc.

Boosting models take advantage of the heuristic information like the classification results during the iterative process and can be only trained in sequential process. Adaboost first took the idea of boosting into practice and more boosting algorithms are designed afterwards like SMOTEBoost [9], MSMOTEBoost [15], RUSBoost [37], AdaboostNC [44], BSIA [49], EUSBoost [16], etc. Both EasyEnsemble and BalanceCascade [28] use Adaboost as their base classifiers and BalanceCascade adjusts the threshold depending on the false positive rate. SPE [29] and MESA [30] are boosting models trained by subsets under-sampled according to hardness distributions [26].

## 3 PROPOSED METHOD

We come up with our ensemble learning model ASE (Anomaly Scor- ing Ensemble) inspired by the strengths and weaknesses of existing methods. Resampling methods have the tendency to ignore some informative instances and discard the original distribution of raw data. Cost-sensitive models need experts in certain fields to provide prior knowledge like a cost matrix so that models can applied a higher penalty to the minority class to reduce the negative impact of high imbalance ratio, which is not feasible in some situations. The main idea of ensemble learning is combining a number of weak learning to reconcile the impact of imbalance ratio, outliers and noise to single classifier [18].

To solve the problems above and take advantage of the strengths of three kinds of solutions, we use anomaly detection algorithms to score all the training samples and we take these scores as the abnormal degree of instances. Then we split different training samples into different bins according to their abnormal degree and we assign a weight to each bin by our ASW (Anomaly Scoring Weight) function. After that, we then resampling from each bin with ASW to construct a subset to train a base estimator. Finally, we combine all base estimators into a strong learner with our CEW (Contamination Entropy Weight) function.

### 3.1 Symbol definition

In this paper, we define majority class $N$ as negative class and minority class $P$ as positive class.

$$P = \{(x, y)|y = 1\}$$  \hspace{1cm} (2)

$$N = \{(x, y)|y = 0\}$$  \hspace{1cm} (3)

And we take Confusion Matrix to help to evaluate the anomaly detection model performance on the training set and the final performance of our ensemble framework.

$A_i$ is the anomaly detection model in the $i$ iteration and $AS_{i,j} = A_i(x_j)$ denotes the anomaly score of the $x_j$. $B_{i,b}$ represents the $b$-th bin in the $i$-th iteration and $ASW_{i,j}$ is the weight of $B_{i,j}$. $C$ is our Contamination function which is relevant to the percentage of outliers of the anomaly detection model.

### 3.2 Anomaly Scoring System

Since under-sampling is easy to suffer from discarding some informative instances and disturb underlying distributions, some try to extract the hidden information in raw data so that they applied
Nearest Neighbor to guide resampling like CNN [20], ENN [45] and NCR [25]. Since Nearest Neighbor is often used in clustering and anomaly detection, we try to apply other advanced algorithms in Anomaly Detection like Isolation Forest [27], SVDD [35], Auto Encoder [47], etc. Anomaly detection models will score the examples and examples whose scores surpass the threshold will be classified as the outliers. In ASE, we used these scores to guide our resampling strategy. Some methods try to assign a weight to every instance, like RUSBoost and AdaboostNC [44]. Others introduce a concept called Hardness Distribution [26, 29, 30] and they use some common functions like Absolute Error, Squared Error or Cross Entropy as their hardness function which try to represent the hardness to classify examples correctly. And then they split all positive samples into different bins and take the mean of all example in a specified bin as the weight of this bin.

Inspired by the idea of instances’ weight and splitting data into bins, now we introduce our own concept called ASW (Anomaly Scoring Weight). Our ASW needs two hyper-parameter $a$ and $b$, $b$ is the number of bins and $a * 100\%$ is the percentile to resample from each bin. We split all training samples into $b$ bins by the anomaly score $A_S$ given by the anomaly detection model $A$ and each bin indicates a certain anomaly level.

$$A_S_{i,j} = A_i(x_j)$$ (4)

$$B_{i,l} = \{(x_j, y_j) | \frac{l-1}{k} \leq A_S_{i,j} < \frac{l}{k}\}$$ (5)

Since our datasets are under high imbalance ratio so a part of the minority class will be regarded as the outliers, which have a greater probability to receive higher anomaly scores from anomaly detection model than most samples in the majority class. However, what makes the imbalance classification intractable is that the majority class usually overlaps with the minority class [12] and there is no a specific boundary between two classes. The overlapping data will seriously affect the performance of the base estimator so we need to pay more attention to these samples.

$$ASW_{i,l} = \frac{\log \frac{1}{|B_{i,l}|}}{\sum_{k=1}^{k} \log (\frac{1}{|B_{i,l}|})}$$ (6)

$$d_{i,l} = \left| \frac{r-0.5}{k} - 1 + c_i \right|$$ (7)

$ASW_{i,l}$ represents the weight of the $l$-th bin according to the $i$-th anomaly detection model and the number of instances needed to be resampled from the majority class of the $l$-th bin is $n_{i,l}$. $d_{i,l}$ implies the distance between the $l$-th bin and the boundary of contamination area. And $c_i$ is the contamination coefficient used when training the $i$-th base estimator.

$$n_{i,l} = a|N| \cdot ASW_{i,l} \cdot \frac{d_{i,l}}{\sum_{l=1}^{k} d_{i,l}}$$ (8)

Then we combine the resampled instances from different bins with all the samples from the minority class to construct a subset which has a lower imbalance ratio than original dataset to train a base estimator.

Figure 2 shows how ASW works to decide the resampling proportion in ASE. We train 50 weak learners with Contamination increasing from 0.05 to 0.40 to construct our ensemble learning model on data set Wine which includes about 5,000 instances and the imbalance ratio is about 26:1. The number of samples in each bin is displayed and we choose the distributions of data in 5 rounds of training to be shown in Figure 2.

### 3.3 Contamination Entropy Weight Ensemble

When constructing weak learners into an ensemble model in many mainstream methods, they will not combine the weak learners directly but get the weighted average of all weak learners. The weight functions are usually relative to the classification results of the base estimators generated in the previous training process [46]. In RUSBoost [37], the pseudo-loss will be calculated to update the weight parameters which will have a great impact on the resampling method in the next iteration and will directly affect the weight of the base estimator trained in this iteration. AdaboostNC [44] tries to access the disagreement degree of the classification with penalty strength and calculates the weight of base estimators by error and penalty. Some factors derived from confusion matrix like the weight of FP and the rate of the quotient of TP and FP instances are applied to update the model in each iteration. In this paper, we propose our weight function $CEW$ (Contamination Entropy Weight).

In each iteration, we change the contamination coefficient of the anomaly detection model, which is relative to the amount of contaminated instances of the dataset. Since the proportion of the outliers is changed, the Recall on the training set will be changed. With higher Recall, our anomaly detection model has a higher performance on the minority class and the minority instances are more possible to be split into the bin with higher $ASW$. In this case, more instances in minority class will be split into bins with higher $ASW$ so the number of instances resampled from these bins will increased. In result, the $n_{i,l}$ where $l$ is more closed to $b$ will...
Table 3: Traditional classifier’s performance on synthetic datasets

| Data set       | Precision | Recall | F1   |
|---------------|-----------|--------|------|
| Overlapping   | 0.038     | 0.003  | 0.005|
| Nonoverlapping| 0.651     | 0.596  | 0.622|

increased, that is to say the base estimators will focus more on more informative instances in the majority class like the overlapping area between the majority and the minority class.

Figure 3: Overlapping and nonoverlapping under high imbalance ratio

Besides imbalance ratio, data overlapping also accounts for the poor performance of existing models dealing with imbalance datasets [12]. Since there is a tiny difference between majority class and minority class, there is no an obvious boundary of two classes and the high imbalance ratio may lead to the model considers a part of minority examples as noise, which seriously makes the performance declined. We use a synthetic data set to demonstrate the impact of overlapping with high imbalance ratio on traditional classifiers. The data set with imbalance ratio 22.5 is synthesized by multivariate normal distribution with 45,000 negative samples and 2,000 positive samples. Figure 3 shows the distributions of two data sets and it is obvious that that the left one suffers from serious overlapping. Table 3 is the performance of decision tree on two synthetic datasets.

The contamination percentage will directly affect the Recall value, but the main idea to attach an anomaly detection model to our framework is not only to detect all the majority class and classify the minority class into a specific bin the first time, but also to balance the proportion of the number of majority class, minority class and the overlapping data in the constructed subsets. In order to handle data overlapping problem, we need our model to pay more attention to the overlapping area in the original dataset. In ASE, we combine the idea of information entropy and confusion matrix to weigh each base estimator and the proposed weight function $CEW$ (Contamination Entropy Weight) is showed as below.

$$CEW_i = C_i \cdot E_i$$  \hspace{1cm} (9)

$CEW$ can be divided into two parts. $C$ is a contamination function relative to Recall, which reveals the anomaly detection model’s ability to detect the minority class exactly. $E$ is a function derivated from information entropy which can quantitatively assess the anomaly model generalization ability on the overlapping area between majority class and minority class.

$$C = \log\left(\frac{|P|}{FN}\right)$$
$$= \log\left(\frac{1}{1 - \text{Recall}}\right)$$ \hspace{1cm} (10)

$$E = -\left(\sum_{i=1}^{k} p_i \log(p_i)\right)$$
$$= - \left(\frac{TP}{TP + FP} \cdot \log\left(\frac{TP}{TP + FP}\right)\right)$$
$$= \left(\frac{FP}{TP + FP} \cdot \log\left(\frac{FP}{TP + FP}\right)\right)$$ \hspace{1cm} (11)

The core idea of information entropy [38] is to quantify the value of information. When there is no enough information concealed in data or something is highly likely to happen, we say that the information entropy in this case is low. When majority class or minority class consist of the most part of the outliers detected by the anomaly detection model, we can regard the result of anomaly detection model can not give enough information for us to find the overlapping area between the majority and minority class and this situation has a low information entropy. On the contrary, when the number of majority class in examples predicted as positive (FP) is closed to the number of minority class in examples predicted as positive (TP), the examples in overlapping area are nearly balanced and we will receive a higher information entropy. Since the overlapping area is more balanced, the weak learner trained in this iteration will have a better generalization ability of the overlapping data so we should assign a greater weight to it.

3.4 ASE (Anomaly Scoring Ensemble Learning)

After discussing our model’s modules in detail, now we will give the general framework of ASE. Firstly, we need an anomaly detection model like Isolation Forest [27], SVDD [35] or Auto Encoder [47] to assign anomaly scores $AS$ to the training data. Then we need to split majority class into $b$ bins according to anomaly scores and we will calculate $ASW$ for each bin. With $ASW$ we can down-sample specific number of instances from each bin and combine these instances with minority class to build a subset which has adjusted the proportion among majority class, minority class and overlapping area. Base classifiers trained by these subsets can suffer less from high imbalance ratio and disruption of the raw data distributions by resampling and have a better generalization ability. In each iteration, the proportions of contamination data are set differently which will affect the resampling strategy directly and we need to quantify each base estimator’s generalization ability so we introduce our weight function $CEW$. $CEW$ consists of two parts which are relative to the ability of the anomaly detection model to find the majority class $C$ and the ability to discover the overlapping area between two classes $E$ respectively.
Algorithm 1 ASE (Anomaly Scoring Based Ensemble Learning)

**Input:** minority class \( P \), majority class \( N \), number of base estimators \( b \), base estimator \( M_i \), anomaly detection model \( A \), number of bins \( k \), resample coefficient \( a \)

**for** \( i = 1 \) to \( b \) **do**
- Train anomaly detection model \( A_i \) with Contamination coefficient \( c_i \) and normalize \( AS_i \)
- Split training set into \( k \) bins w.r.t. \( AS_i \)
- Compute \( AS_i \) for each bin and under-sample specific number of majority class from each bin to construct subset \( s_i \)
- Train base estimator \( M_i \) with subset \( s_i \) and minority class \( P \)
- Compute \( CEW_i = C_i \cdot E_i \) for \( M_i \)
**end for**

Ensemble base estimators \( ASE = \sum_{i=1}^{b} M_i \cdot CEW_i \)

4 EXPERIMENT

4.1 Evaluation Criterion

We use some common criterions in imbalanced learning area based on confusion matrix. If the classification model considers all the testing samples as majority class, the model will still get a high accuracy score because of the high imbalance ratio. Precision and recall are usually used to evaluate models’ performance on the minority class. So we take accuracy, precision, recall, ROCAUC and F1 to evaluate our model performance.

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{12}
\]

\[
\text{Precision} = \frac{TP}{TP + FP} \tag{13}
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \tag{14}
\]

\[
\text{ROCAUC} = \text{Area Under the Receiver Operating Characteristic Curve} \tag{15}
\]

\[
F_1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{16}
\]

4.2 Datasets

There are many application scenarios for imbalanced classification and various algorithms are widely used in different industries, like finance, manufacturing, scientific research and medicine. There are a number of areas suffer from data imbalance in real-life situations such as risk prediction, financial assessment, loan default, credit card fraud, network intrusion detection, fraud detection, product quality inspection and disease diagnosis. Therefore, we selected several datasets which are representative in each scenario to evaluate our proposed framework.

- **Credit Fault:** The dataset (Credit Card Fraud Detection) [11] contains transactions made by credit cards in September 2013 by European cardholders. Each entity has 30 features, which are the result of a PCA transformation and this data set contains 492 frauds out of 284,807 transactions.
- **Credit:** Give Me Some Credit is a data set about credit scoring using in Kaggle featured prediction competition. We randomly select 150,000 instance with imbalance ratio 13.96:1 for our experiment. Each instance has 11 features about credit card users’ personal information.
- **ISOLET:** ISOLET (Isolated Letter Speech Recognition) is a real-world data set generated by 150 subjects spoke the name of each letter of the alphabet. ISOLET is a high-dimension data set with 617 attributes, containing 7,797 instances and 600 instances among which are minority class.
- **KDD2004:** This data set is provided by KDD Cup 2004, focusing on predicting which proteins are homologous to a native sequence. This data set has 145,751 instances with 74 features and the imbalance ratio 111:1.
- **Mammography:** Mammography is the most effective method for breast cancer screening available today. Each instance in Mammography (Mammographic Mass Data Set) only contains 6 features and it has only 260 malignant instances out of 11,183 records.
- **Wine:** Wine Quality Data Set is a UCI [4] data set, including two data sets related to red and white variants of the Portuguese “Vinho Verde” wine. Since there are more normal wines than excellent or poor ones, this dataset has an imbalance ratio about 26:1 and 4,898 instances with 11 features.
- **Letter:** There are a large number of black-and-white rectangular pixel displays as 26 capital letters in UCI data set Letter Recognition. This data set has 20,000 instances with 16 features and the imbalance ratio 26:1.
- **Ozone Level:** UCI dataset Ozone Level contains 2,536 instances with 72 dimensions, which were collected from 1998 to 2004 at the Houston, Galveston and Brazoria area. This imbalanced dataset with imbalance ratio 34:1 quantifies two ground ozone level.

4.3 Experiment Design and Result

We first use isolation forest as the anomaly detection model and decision tree as the base estimator in our experiment. Apart from that, the depth of all decision trees are set as 10 and all ensemble learning models contain 50 base classifiers. In order to test out the performance of ASE, we use 6 datasets, Credit Fault, ISOLET, KDD2004, Mammography, Letter and Ozone Level to compare ASE with 12 existing methods, including resampling methods and ensemble learning models which are widely used in imbalanced datasets.
In detail, the models we select including Decision Tree, SMOTE, Random Forest, GBDT, AdaBoost, UnderBagging, OverBagging, EasyEnsemble, BalanceCascade, SMOTEBoost, RUSBoost and SPE.

The results are shown in Table 4 and ASE gets the highest scores of Accuracy, AUC and F1 among all 13 compared methods in 6 representative datasets in various scenarios, where the data usually suffers from high imbalance ratio. Compared with the second-best F1 score in Ozone Level and Mammography, ASE achieves 181% and 23% performance gain.

The experiment results show that ASE is well-designed and has an exceeding ability to work out the data skewing problem than existing methods. The fluctuation of imbalance ratio, the scale of datasets and the changes in application scenarios demonstrate ASE not only has high performance but also robustness.

Above experiment uses Decision Tree as the base classifier and Isolation Forest as the anomaly detection model. In order to illustrate the excellent design philosophy of ASE, we change the base classifiers and use various anomaly detection algorithms in ASE.

To compare ASE performance while using different base classifiers, We then use Decision Tree, Logistic Regression, SVM, KNN and MLP in data sets KDD2004, Credit and Wine to compare ASE with SMOTE, SPE, EasyEnsemble and BalanceCascade and use F1 as evaluation criteria. As shown in Table 6, ASE gets all the highest F1 which demonstrates that ASE is not only limited to a specific classifier, this ensemble learning framework has a well generalization ability which can be applied to various classifiers.

Apart from changing the base classifiers, experiment which combines different anomaly detection models with ASE has been conducted. We use some representative and efficient anomaly detection models including Isolation Forest, KNN, OCSVM, Auto Encoder and ROD (Rotation-based Outlier Detection) as anomaly scoring part of ASE.

- **Isolation Forest** [27] randomly selects a value between the minimum and maximum values to split the data into partitions since anomalous data are few and different.
Table 6: Performance of ASE with Different Base Classifiers

| Data Set | Classifier | None | SMOTE | SPE | Balance | Easy | ASE  |
|----------|------------|------|-------|-----|---------|------|------|
| DT       | 0.798      | 0.345| 0.841 | 0.743| 0.304   | 0.866|
| LR       | 0.778      | 0.227| 0.763 | 0.660| 0.213   | 0.778|
| SVM      | 0.643      | 0.255| 0.740 | 0.615| 0.121   | 0.747|
| KNN      | 0.560      | 0.239| 0.148 | 0.178| 0.098   | 0.599|
| MLP      | 0.828      | 0.764| 0.811 | 0.334| 0.705   | 0.828|
| KDD2004  | DT         | 0.288| 0.340| 0.357| 0.179   | 0.323| 0.363|
|          | LR         | 0.041| 0.158| 0.160| 0.133   | 0.174| 0.245|
|          | SVM        | 0.126| 0.300| 0.140| 0.272   | 0.360| 0.380|
| Credit   | KNN        | 0.667| 0.203| 0.198| 0.189   | 0.111| 0.236|
| Wine     | MLP        | 0.096| 0.203| 0.198| 0.189   | 0.111| 0.236|

Table 7: Performance of ASE with Different Anomaly Detection Model on Data Set Wine

|                | DT      | UnderBagging | BalanceCascade | SPE | Iforest-ASE | OCSVM-ASE | KNN-ASE | AE-ASE | ROD-ASE |
|----------------|---------|--------------|----------------|-----|-------------|-----------|---------|--------|---------|
| Accuracy       | 0.855   | 0.872        | 0.846          | 0.835| 0.958       | 0.928     | 0.974   | 0.957  | 0.971   |
| Precision      | 0.130   | 0.182        | 0.155          | 0.151| 0.448       | 0.338     | 0.649   | 0.492  | 0.592   |
| Recall         | 0.531   | 0.745        | 0.737          | 0.789| 0.703       | 0.855     | 0.657   | 0.701  | 0.605   |
| AUC            | 0.699   | 0.811        | 0.793          | 0.813| 0.835       | 0.893     | 0.822   | 0.834  | 0.794   |
| F1             | 0.208   | 0.292        | 0.256          | 0.254| 0.545       | 0.472     | 0.651   | 0.576  | 0.595   |

- **KNN** [3] is a popular algorithm widely used in classification, anomaly detection which assumes that outliers are usually stay away from the cluster of similar instances.
- **OCSVM** [31] is an unsupervised outlier detection which can estimate the support of a high-dimensional distribution and is based on the premise that outliers will cluster in a dense region in the origin dataset.
- **Auto Encoder** [47] can be used to detect anomaly by encoding and compressing the data into the lower dimensions and then decode to reconstruct the data.
- **ROD** [2] is a parameter-free algorithm which uses 3D-vectors to represent the raw data and uses Rodrigues rotation formula for scoring the data to find the outliers.

Decision Tree is selected as the base classifier trained on data set Wine and the results are shown in Table 7. We compare ASE with SMOTE, EasyEnsemble, BalanceCascade, UnderBagging, OverBagging and SPE but we only show the compared models with highest performance including UnderBagging, OverBagging and SPE because of the layout.

Since the number of base classifiers is the key determinant of the performance of ensemble learning models, we compare the training process of ASE with other ensemble learning models, including UnderBagging, OverBagging, EasyEnsemble, BalanceCascade and SPE. We choose dataset Wine and Decision Tree as the base classifier.

Figure 4 shows the chance of the ROC and F1 when training ensemble learning models. ASE nearly performs best during all the training process. ASE performs well with limited base classifiers and converges faster than mainstream ensemble learning models.

5 CONCLUSIONS

Highly imbalanced, data-overlapping, large scale are common intractable problems in many real-life scenarios and machine learning methods applied in these scenarios suffer from poor performance. In this paper, we propose an innovative ensemble learning framework, Anomaly Scoring Based Ensemble Learning. Since our model can evaluate the overlapping area of majority class and minority class efficiently, the ensemble model has a better generalization.
ability on imbalanced dataset with overlapping. Experiments on several datasets in scenarios like finance, medicine and industry have been conducted and the performance and robustness of our model have been tested out. And we believe that our ensemble learning model can be applied to various real-life scenarios.

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