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Multi-class Classification of Imbalanced Intelligent Data using Deep Neural Network

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Abstract

In recent years, studies in the field of deep learning have made significant progress. These studies have focused more on datasets with balanced classification, and less research has been done on imbalanced datasets, which are of great importance in the real world and present significant challenges for classification. This article studies the problem of classifying imbalanced data, introduces dynamic sampling for deep neural networks, investigates the imbalanced multiclass problem, and proposes a dynamic sampling method for deep learning. In our proposed method, all samples are fed to the current deep neural network for each training iteration, and the accuracy, precision, and mean error of the deep neural network are estimated. The proposed method dynamically selects informative data for training the deep neural network. Comprehensive experiments were conducted to evaluate and understand its strengths and weaknesses. The results of 13 imbalanced multiclass datasets show that the proposed method outperforms other methods, such as initial sampling techniques, active learning, cost-sensitive learning, and reinforcement learning.

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1. Introduction

The challenge of imbalanced data spans various domains, including vital fields like medicine and robotics [1]. This data type can carry unexpected errors and grave consequences in data analysis, particularly in data classification. For example, in clinical data [2], the majority of individuals are healthy, while only a small proportion are sick. Consequently, healthy individuals constitute the majority, while patients represent the minority. Misdiagnosing a patient as healthy can result in treatment delays and serious repercussions. Methods such as cost-sensitive learning, initial and adaptive sampling techniques [3], and active learning can enhance classification performance on imbalanced data. Moreover, recent advancements in graph theory have exhibited promising potential in addressing the challenges posed by imbalanced data. Graph-based classification algorithms, for instance, capitalize on the underlying graph structure of imbalanced datasets to make accurate predictions. By incorporating graph-based measures and algorithms like graph-based clustering or label propagation, these methods can effectively leverage the relationships and connectivity patterns between instances, leading to improved classification accuracy, particularly for imbalanced datasets [4]. Failure to handle imbalanced data with precision and accuracy significantly increases the likelihood of misclassifying minority classes, thereby giving rise to significant issues. Consequently, enhancing the accuracy in predicting minority classes within imbalanced data assumes paramount importance.

In robotics, imbalanced data classification techniques can be valuable for various tasks such as object recognition, gesture recognition, anomaly detection, and fault diagnosis [5].

The aim of this paper is to propose a method to increase the balanced accuracy of data and overcome the problem of class imbalance by balancing the data at the classification stage. To achieve this goal, the effectiveness and efficiency of the proposed model are compared and evaluated with other existing models.

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The main objective of this paper is to provide a deep learning neural network-based model to improve the performance of multiclass classification of imbalanced data. This model enhances the classification results of multi-class data in the presence of outliers and noise. The proposed model reduces sensitivity to class imbalance, and the results of the final algorithm are expected to be promising and demonstrate the progress of the algorithm.

In this paper, we investigate the problem of intelligent multi-class classification of imbalanced data using deep neural networks. Various methods for solving the problem of imbalanced data are examined by collecting imbalanced data from the UC Irvine website. In the first section, the research background and previous work in this field are reviewed. In the second section, the data used, the simulation environment, and the implementation method of the proposed approach are explained. Then, in the third section, the results obtained from the implementation of the proposed approach are presented, and in the last section, some conclusions are discussed.

1.1. Research Contribution

1. Study of imbalanced data classification: The article addresses the problem of classifying imbalanced data and recognizes the complexities associated with imbalanced multiclass problems.
2. Introduction of dynamic sampling: The research proposes a novel method called dynamic sampling for deep neural networks to tackle imbalanced data classification.
3. Evaluation and comparison: The proposed method is rigorously evaluated and compared with other existing techniques, including initial sampling techniques, active learning, cost-sensitive learning, and reinforcement learning.

2. Research Background

Imbalanced data is often present in the diagnosis of rare diseases, network attacks, the identification of crimes and bank fraud, text mining and so on. Therefore, the problem of imbalanced classes has recently received attention from researchers in the field of data analysis. In fact, providing methods for classifying imbalanced data is expected to lead to desired results for researchers. Classifying imbalanced data always causes problems because standard machine learning algorithms usually have poor performance. The problem of class imbalance has been studied by many researchers through different methods [6] such as under-sampling [7], remove some data from the majority class [8], over-sampling [9], deals with creating balance in imbalanced data by adding artificially generated [10, 11] or repeated samples to the minority class [12]. Some other methods are graph-based oversampling which utilize graph theory to generate synthetic instances for the minority class in imbalanced datasets [13]. In addition to initial sampling models, another category of models called cost-sensitive models is also important for solving class imbalance problems. The class imbalance problems can be done as a cost-sensitive problem, and we can do that by adjusting the appropriate cost matrix and existing models [14, 15]. The bagging method [16] has been proposed to reduce model variance. In this method, several models are created using the same algorithm on random subsets of the data, and their prediction results are combined using majority voting or weighted voting. The Boosting method [17–20] has also been proposed to improve accuracy and reduce classification error. In this method, weak models are created using the same algorithms, and their prediction results are combined at different stages using weight combining. On the other hand, active learning can be useful to design models to solve class imbalance problems. This method is based on obtaining useful samples as much as possible, removing repeated samples, and obtaining better power using smaller training data. Ertekin et al. proposed an active learning model based on SVM for class imbalance problems [21]. Most of the advanced models are generally designed for binary classification problems [22], but the effectiveness in multiclass problems has not been studied well. On the one hand, developing reinforcement learning and active learning models for multiclass problems is not easy, and cost-sensitive and sampling-sensitive models are available for both binary and multiclass problems [7, 23], but defining the initial sampling ratio or misclassification cost in these two models is not an easy task using the algebraic structures to simplify this task may be useful [24]. In fact, studies have shown that most sampling models are not effective in multiclass problems and have bad effects on problems that may have many classes [17]. Furthermore, although some recent research has made progress in multiclass classification problems, the issue of class imbalance has not been solved well. Therefore, it is necessary to design a model that directly solves the class imbalance problem in multiclass samples. Use of the ensemble learning method has received a lot of attention from researchers and users because it improves the accuracy and performance of classification models. Ensemble learning methods include Bagging, Boosting [17, 25], Stacking, and Blending. In Stacking method, a few models are used as inputs to a Meta model. This Meta model tries to produce the final output using the results of previous models. In Blending method, the training data is divided into two parts, and the first part is used to train several models, the second part is used to produce outputs from the trained models. Then,

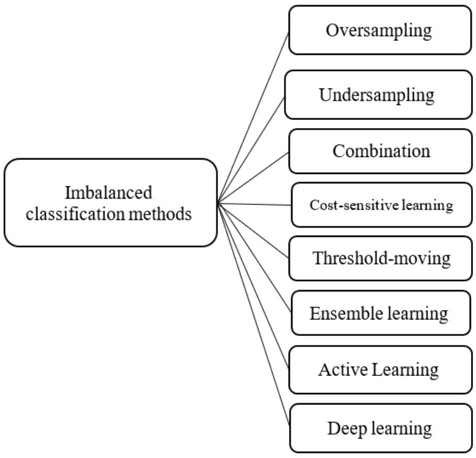

Figure 1. some of the most used models for imbalanced classification

the generated outputs from the second part are used to train a Meta model with the training data from the second part. Active learning model first trained with the training data as usual. In the next step, an active learning model is trained for each training class using the training data. In this step, instead of training one model for the entire data, a separate model is trained for each class. Then in the testing phase, the appropriate model is applied to each class based on the probability of data allocation to that class. This approach can increase the classification accuracy for smaller categories and improve the model performance. Figure 1 has shown some of the most used models for imbalanced classification.

3. Proposed Method

As previously mentioned, imbalanced data can give rise to critical errors that hold significance in various fields, including medicine and robotics. The presence of imbalanced data can lead to biased models, limited generalization, and reduced performance in accurately addressing real-world challenges [26, 27]. Addressing this issue is essential to ensure reliable and effective solutions in these important domains. In this section, we are going over a new model for classifying imbalanced data that uses Deep Learning (DL) and call this improved model the Deep Learning Neural Network. In the proposed model in this research, we dynamically select data containing useful information for training, and then we feed it into the deep neural network. In fact, dynamic sampling selects samples dynamically during the process [23]. No samples are removed before starting the process to prevent information loss, and samples are dynamically selected to prevent repeated information and use the training data better. Graph theory can be utilized to extract meaningful features from imbalanced datasets. By representing the data instances as nodes and their relationships as edges, graph-based feature extraction [28] methods can capture the structural information and connectivity patterns in the data. These extracted features can be used to enhance the classification performance on imbalanced data [29].

3.1. Project phases

Understanding the research goal: In this stage, the purpose of the research and the factors affecting it are identified.

(i) Data Usage phase: Using imbalanced data sets collected;

(ii) Data Preparation Phase: preprocessing data, cleaning, transforming, merging data, and sampling data to apply classification techniques to imbalanced data using dynamic, initials, or other sampling algorithms;

(iii) Model building phase: In this stage, we focus on prediction and modeling based on data preparation. We use the proposed algorithm of neural network-deep learning;

(iv) Evaluation phase: In this stage, we evaluate and compare the model to see if we have achieved the goal or not. In some cases, we may need to repeat certain stages to achieve the goal;

(v) Implementation phase: We reach this stage when we have achieved the goal. This phase involves putting the developed model or solution into action in a real-world setting;

The steps of the improved deep learning neural networks are summarized in Figure 2.

3.2. Variables under study and measurement criteria

In this paper, accuracy is used as an evaluation metric for classifier performance. It is a good measure for assessing the efficiency of classifiers when the distribution of data is balanced. However, it is not suitable when the data distribution is uneven. For example, consider a binary classification with a distribution of $1:99$. If the classifier assigns all samples to the majority class, the accuracy of classification will become greater (99%). But this classifier will not be useful in practice. Instead of accuracy, the area under the receiver operating characteristic (ROC) curve (AUC) is used as an evaluation metric for classifier performance. AUC is generally applicable in binary classification problems. In [30], AUC extended to multiclass problems and proposed a measurement tool

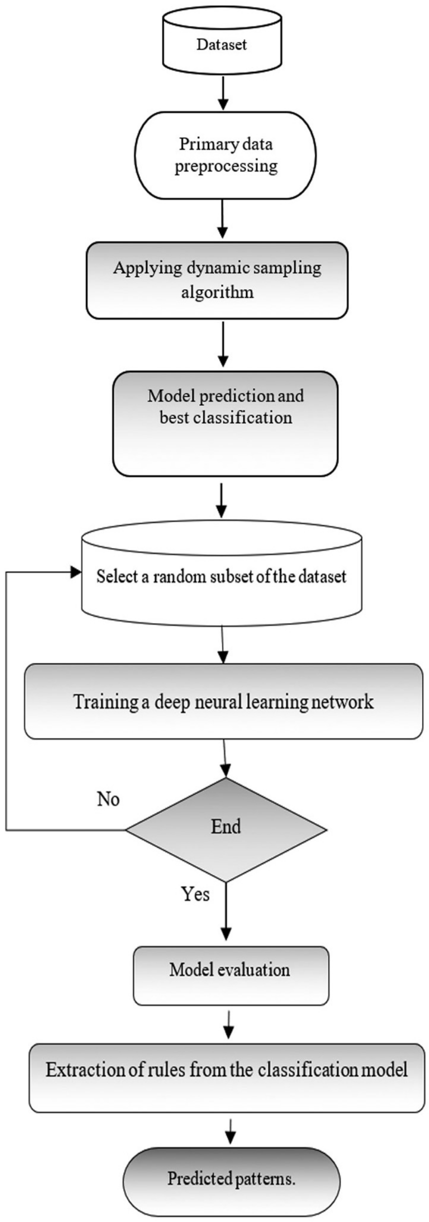

Figure 2. The framework of the improved deep learning neural networks

called M for multiclass classification problems. This measurement tool, MAUC, inherits many measures from AUC and has been used in evaluating multiclass classification problems. In addition to AUC, geometric mean (G-mean) has also been used as another measure for accurate classification performance evaluation. G-mean is defined as follows:

$$G_{mean} = \prod_{i=1}^{m} (\frac{tr_i}{n_i})^{1/m}$$

Where m is the number of layers, n_i is the number of samples in class i, and Tr_i is the number of correctly classified samples in class i. Furthermore, to observe the different performances of each class, the its AUC is calculated separately. The AUC of each class can be written as:

$$AUC = \frac{1}{c-1} \sum_{j \neq i} A(i, j)$$

$A(i, j)$ represents the value of AUC between class i and class j. The AUC value for each class is shown on the dataset. Experiments were performed on several imbalanced multiclass datasets such as Ecoli, Soybean, Statlog (satellite), letter-recognition, etc. from the UCI machine learning repository. It should be noted that the execution time for each method and algorithm is recorded in the training software. The confusion matrix is also one of the metrics that provides good information about the performance of a classifier. This metric is a 2×2 matrix, each element of which includes one of the following indices. The main matrix is presented in Table 1. In this matrix, we will have 4 elements as follows: TP: True positive rate, the percentage of positive samples that are correctly classified, FP: The rate of false positive samples, the percentage of positive samples that have been incorrectly classified, TN: The rate of true negative samples, the percentage of negative samples that have been correctly classified, FN: The rate of false negative samples, the percentage of negative samples that have been incorrectly classified. By creating this matrix, accuracy can be calculated as:

$$Accuracy = \frac{(TP + TN)}{(TN + FN + TP + FP)}$$

Note that the independent variable in our study is the number of classes, and the dependent variable is the area under the curve (AUC), accuracy, time, and geometric mean (G-mean).

3.3. Research Data

In this paper, first we obtain around 13 imbalanced databases from the UCI machine learning repository website [31]. Then, data preprocessing including steps such as managing missing values, transforming data, managing outlier data, data discretization, removing inconsistent records, and dimensionality reduction are applied on the dataset accordingly. Finally, using dynamic sampling and suitable classification algorithms, the imbalanced data are classified. For this research, Excel software is used for data preprocessing and RapidMiner software is used for implementing data mining algorithms. The general specifications of the dataset used in this research, including the number of samples, number of features, and number of classes, are shown in Table 2.

Table 1. Confusion Matrix

Type of Class	Predicted class		
		Normal	*Abnormal*
Real class	Normal	TP	FN
	Abnormal	FT	TN

Table 2. Research Datasets Information

Data Set	*Classes distribution*	*Number of classes*	*Number of features*	*Sample size*
Abalone	4177	8	18	15: 57: 115: 259: 391: 568: 689: 634: 487 267: 203: 126: 103: 67: 58 :42: 32: 26
Balance Scale	625	4	3	49: 288: 288
Car Evaluation	1728	6	4	1210: 384: 65: 69
Contraceptive Method Choice	1473	9	3	629: 333: 511
Dermatology	366	34	6	112: 61: 72: 49: 52: 20
Echoli	366	6	5	143: 77: 35: 20: 52
Glass	214	9	4	70: 76: 17: 29
Letter-recognition 1	20000	16	26	10: 766: 736: 805: 768: 775: 773: 734: 755: 747: 739 761: 792: 783: 753: 803: 783: 758: 748: 796: 813: 764: 752: 787: 786: 734
Nursery	12960	8	4	4266: 4320: 328: 4044
Soybean	661	35	17	20: 20 :20: 88: 44: 20 :20: 92:20: 20 :20: 44: 20: 91: 91: 15: 16
Splice-junction	3190	60	3	767: 768: 1655
(Stalogs)Satellite	6435	36	6	1533: 703: 1358: 626: 707: 1508
Allbp (thyroid allhypo)	3770	27	3	3481: 194: 95

3.4. Data preprocessing

After downloading the datasets, data preparation and preprocessing should be performed since the other research steps are based on these data. To improve the quality of data for data mining operations, various preprocessing operations were performed on the available datasets. The research data were examined for missing values, outlier data, meaningless columns, data types for classification, and standardization of data.

3.5. Implementation of algorithms on data

The proposed algorithm is implemented on standardized data and its results are also kept for comparison with other competing methods. The proposed algorithm is implemented in the RapidMiner software environment. The process is illustrated in Figure 3.

At this stage, the data was dynamically sampled during the process and trained by a Deep Learning algorithm. The sampled data goes through a loop of 100 Epochs and is validated by the Validation Cross operator, which consists of two sets: Train and Test. The data is divided into these two sets with a ratio

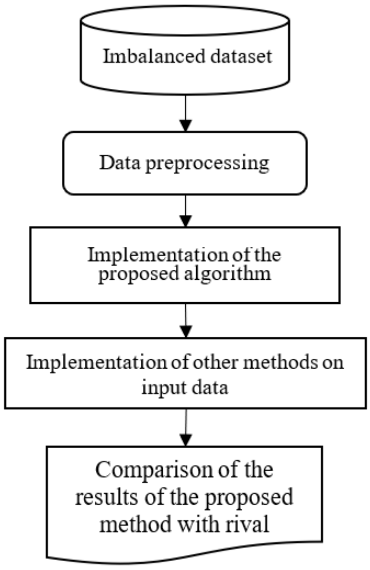

Figure 3. The process of implementation

of 80% for training and 20% for testing, although this ratio can be adjusted. Our model has 5 hidden layers and 20 neurons. After constructing the Deep Learning structure, our model learns from the training data by running 10 training sessions, each resulting in a different number that is averaged to produce the result. The obtained results include accuracy, classification error, precision, recall, mean squared error, and time. Table 3 shows all the results (in percentages) obtained from the Deep Learning model on 13 datasets.

Now the proposed method of dynamic or random sampling and deep neural network is compared with other existing methods. The existing methods include MLP, Neural Network, and Decision Tree models, which have been implemented and their results are presented in the tables 4, 5, 6 and 7.

In Table 4, the results of implementing MLP model with 10 repetitions on 13 datasets are shown.

Table 5 presents the results of Implementing a Neural Network with 5 Hidden Layers and 10 Iterations on a Dataset of 13.

The results of implementing a decision tree with a maximum depth of 20 on our 13 datasets are listed in Table 6 .

4. Comparing the Proposed Method with Other Methods

In this section, we compare the accuracy of deep learning methods with other methods such as MLP, neural network, and decision tree. In the columns, values with underline or bold indicate that the DL method has significantly outperformed the other methods, with values ranging from 90 to 100 percent being highlighted in bold. Additionally, this table indicates that the DL model demonstrates the highest value compared to the other methods. Table 7 shows the accuracies of each dataset when we apply different methods to it.

As it is shown in Figure 4, a significant difference in the average accuracy results across the datasets is observed, with the highest value belonging to the proposed method. The mean accuracy of these 4 methods was calculated as 84.21769, 74.38385, 69.02, and 65.17077, respectively.

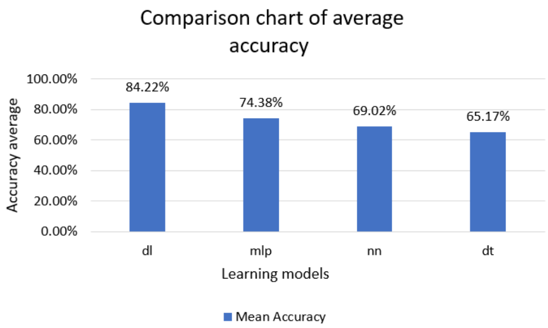

Figure 4. Average Accuracy of the Proposed DL Method Compared to Other Methods

The average precision values are calculated and presented in Table 8. In this table, we display the precision values for the 13 datasets so that we can compare the average precision of each method for each of the 13 datasets.

From Table 8, compared to the other 3 models, the DL model has higher accuracy, and there is a significant difference in accuracy between the proposed method and the others.

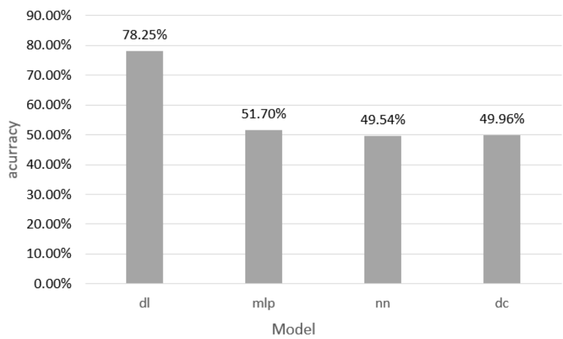

Figure 5. Average Precision, DL Proposed Method Compared to Other Methods

Table 3. Results of implementing the Deep Learning model with 5 layers, each with 20 nodes and 10 iterations

Data Set	*Accuracy*	*Classification Error*	*Recall*	*Precision*	*RMSE*	*Time(seconds)*
Abalone	53.7%	46.3%	54.18%	88.89%	0.561	621
Balance Scale	96.8%	3.2%	97.72%	57.41%	0.151	18
Car Evaluation	98.55%	1.45%	93.36%	98.41%	0.081	49
Contraceptive Method Choice	38.98%	61.02%	33.33%	12.99%	0.781	45
Dermatology	97.26%	2.74%	96.96%	96.87%	0.132	14
Echoli	85.07%	14.93%	14.93%	67.8%	0.382	17
Glass	100%	0%	83.33%	83%	0.006	7
Letter-recognition 1	88.55%	11.46%	87.89%	87.92%	0.324	394
Nursery	95.4%	4.6%	74.18%	69.56%	0.187	215
Soybean	100%	0%	100%	100%	0	2
Splice-junction	57.37%	42.63%	40.4%	85.4%	0.651	209
(Stalogs)Satellite	84.75%	15.25%	82.6%	82.5%	0.38	68
Allbp (thyroid allhypo)	98.4%	1.96%	97.46%	86.48%	0.136	109

Table 4. Results of implementing MLP model with 10 repetitions on 13 datasets

Data Set	*Accuracy*	*Classification Error*	*Recall*	*Precision*	*RMSE*	*Time(seconds)*
Abalone	45.96%	54.04%	51.33%	45.77%	0.624	4
Balance Scale	88.8%	11.2%	63.29%	59.67%	0.33	2
Car Evaluation	79.92%	20.08%	63.28%	56.88%	0.409	2
Contraceptive Method Choice	45.7%	54.3%	39.75%	41.01%	0.648	2
Dermatology	96.36%	3.64%	96.08%	96.97%	0.193	4
Echoli	86.14%	13.8%	55.18%	51.42%	0.396	2
Glass	87.5	12.5	67.91	63.63	0.295	2
Letter-recognition 1	35.95%	64.05%	35.99%	36.05%	0.795	5
Nursery	68.2%	3.8%	47.98%	47.84%	0.532	2
Soybean	100%	0%	0%	0%	0.154	4
Splice-junction	51.25%	48.75%	50%	26.63%	0.503	20
(Stalogs)Satellite	86.75%	13.25%	85.98%	84.58%	0.328	79
Allbp (thyroid allhypo)	94.46%	5.54%	54.71%	61.6%	0.228	42

Table 5. Results of Implementing a Neural Network with 5 Hidden Layers and 10 Iterations on a Dataset of 13

Data Set	*Accuracy*	*Classification Error*	*Recall*	*Precision*	*RMSE*	*Time(seconds)*
Abalone	100%	0%	50%	50%	Unknown	0
Balance Scale	46.4%	53.6%	33.33%	15.47%	0.219	6
Car Evaluation	72.78%	27.22%	31.53%	39.78%	0.469	2
Contraceptive Method Choice	4.75%	95.25%	3.5%	2.86%	0.966	2
Dermatology	99.09%	0.91%	99.02%	99.12%	0.121	2
Echoli	84.16%	15.84%	53.85%	49.45%	0.411	0
Glass	93.75%	6.25%	89.36%	92.16%	0.24	0
Letter-recognition 1	48.83%	53.17%	46.97%	46.33%	0.719	2
Nursery	71.83%	28.17%	53%	52.01%	0.485	0
Soybean	50%	50%	50%	34%	0.701	0
Splice-junction	51.93%	48.07%	33.33%	17.31%	0.625	0
(Stalogs)Satellite	79.5%	20.5%	78.28%	79.16%	0.419	4
Allbp (thyroid allhypo)	94.24%	5.74%	48.97%	66.4%	0.221	2

As Figure 5 shows, the highest accuracy is attributed to the proposed DL model, and there is a significant difference compared to other methods. However, in terms of execution time, unfortunately, the DL model

Table 6. Results of Implementing a Decision Tree with Maximum Depth of 20 on a Dataset of 13

Data Set	*Accuracy*	*Classification Error*	*Recall*	*Precision*	*RMSE*	*Time(seconds)*
Abalone	12.42%	23%	25%	7.12%	0.069	2
Balance Scale	74.33%	54.7%	30.23%	57.64%	0.219	0
Car Evaluation	73.17%	58.22%	31.53%	38.99%	0.469	3
Contraceptive Method Choice	46.15%	57.25%	41.04%	2.86%	0.966	3
Dermatology	94.55%	10.91%	99.02%	95.83%	0.121	3
Echoli	85.15%	25.70%	53.85%	52.17%	0.411	9
Glass	96.88%	60.69%	89.36%	96.6%	0.24	0
Letter-recognition 1	22.27%	53.17%	46.97%	15.84%	0.719	69
Nursery	82.87%	22.17%	53%	61.23%	0.485	2
Soybean	35.71%	69%	50%	8.93%	0.701	6
Splice-junction	51.93%	29.06%	33.33%	17.31%	0.625	69
(Stalogs)Satellite	73.83%	23.58%	78.28%	74.39%	0.419	4
Allbp (thyroid allhypo)	97.96%	9.47%	48.97%	82.33%	0.221	4

Table 7. Table of Accuracies of 13 datasets

Data Set	*DL*	*MLP*	*NN*	*DT*
Abalone	53.7%	45.96%	100%	12.42%
Balance Scale	96.8%	88.8%	46.4%	74.33%
Car Evaluation	98.55%	79.92%	72.78%	73.17%
Contraceptive Method Choice	38.98%	45.7%	4.75%	46.15%
Dermatology	97.26%	96.36%	99.09%	94.55%
Echoli	85.07%	86.14%	84.16%	85.15%
Glass	100%	87.5%	93.75%	96.88%
Letter-recognition 1	88.55%	35.95%	48.83%	22.27%
Nursery	95.4%	68.2%	71.83%	82.87%
Soybean	100%	100%	50%	35.71%
Splice-junction	57.37%	51.25%	51.93%	51.93%
(Stalogs)Satellite	84.75%	86.75%	79.5%	73.83%
Allbp (thyroid allhypo)	98.4%	94.46%	94.24%	97.96%

Table 8. Comparison Table of Precision for Different Models and Display of the Best Model

Data Set	*DL*	*MLP*	*NN*	*DT*
Abalone	53.7%	45.96%	100%	12.42%
Balance Scale	96.8%	88.8%	46.4%	74.33%
Car Evaluation	98.55%	79.92%	72.78%	73.17%
Contraceptive Method Choice	38.98%	45.7%	4.75%	46.15%
Dermatology	97.26%	96.36%	99.09%	94.55%
Echoli	85.07%	86.14%	84.16%	85.15%
Glass	100%	87.5%	93.75%	96.88%
Letter-recognition 1	88.55%	35.95%	48.83%	22.27%
Nursery	95.4%	68.2%	71.83%	82.87%
Soybean	100%	100%	50%	35.71%
Splice-junction	57.37%	51.25%	51.93%	51.93%
(Stalogs)Satellite	84.75%	86.75%	79.5%	73.83%
Allbp (thyroid allhypo)	98.4%	94.46%	94.24%	97.96%

takes the longest time, while competitor methods are executed in the shortest time.

5. Conclusion

To determine suitable classification algorithms, first, the effective criteria for feature valuation were examined, and then the percentage of estimation based on different classification algorithms was separately calculated for each of these criteria. Among the selected algorithms, the deep learning algorithm showed the highest evaluation based on the criteria of accuracy(84.22%), precision (78.25%), time, and classification error, and the proposed model had the higher accuracy and performance. Furthermore, after calculating accuracy, precision, size, and error rate according to the following equation, the obtained results showed that the proposed model reduces sensitivity to class imbalance. This work holds significant potential for application in guarding path [32, 33], robotic activities, specifically in the areas of UAV image analysis and AGV classification. In robotics, imbalanced data classification techniques can be valuable for various tasks such as object recognition, gesture recognition, anomaly detection, and fault diagnosis [34].

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