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Optimizing Imbalanced Data Classification The OWA-ELM Approach

,K.Triveni[1] ,Mr.N.Sravankumar[2]

[1]PG Student, Vemu Institute of Technology, P. Kothakota

[2]Assistant Professor, Vemu Institute of Technology, P. Kothakota, AP

ABSTRACT

In the realm of machine learning, the Extreme Learning Machine (ELM) excels in classification and regression but falters with imbalanced data. To address this, we introduce OWA-ELM, an enhanced ELM algorithm with output weight adjustment. OWA-ELM strategically adjusts connection weights to favor minority classes, improving their classification accuracy without compromising majority class performance. Furthermore, we integrate OWA-ELM with the deep learning SMOTE algorithm to automatically synthesize similar data, addressing data imbalance more effectively. Our extended OWA-ELM with SMOTE outperforms other algorithms, achieving higher FSCOREs and demonstrating superior classification performance on imbalanced datasets.

Keywords: Imbalanced Data, OWA-ELM

INTRODUCTION

In machine learning classification applications, imbalanced datasets pose significant challenges across diverse fields such as computer vision, medical science, and industry. Traditional classifiers often exhibit bias towards majority classes, overlooking minority classes due to their inherent assumption of balanced sample distribution. Extreme Learning Machine (ELM), a rapid and efficient neural network, despite its widespread use in various applications, struggles with imbalanced data, leading to suboptimal classification results favoring majority classes. Several algorithms like WELM, LW-ELM, and CCR-ELM have been proposed to enhance ELM's performance on imbalanced datasets by introducing weighted schemes, regularization parameters, and cost-sensitive approaches. However, these approaches either lack efficiency, introduce complexity, or require extensive parameter tuning. Addressing these limitations, our project aims to introduce a novel algorithm that leverages the strengths of ELM while effectively handling imbalanced data for improved classification accuracy.

LITERATURE SURVEY

S. Dhar and V. Cherkassky*et al*

AsThe authors introduce an extension to the Universum-support vector machine (U-SVM), a learning methodology tailored for analyzing high-dimensional data with a high feature-to-sample ratio. While U-SVM has shown promise in handling sparse high-dimensional datasets, previous studies primarily focused on balanced datasets with uniform misclassification costs. This paper innovatively extends U-SVM to accommodate varying misclassification costs, enhancing its applicability in real-world scenarios with imbalanced data. Practical conditions for optimizing this cost-sensitive U-SVM are delineated, supported by empirical comparisons demonstrating the efficacy of the proposed approach in diverse learning settings.

Z. Li, K. Kamnitsas, and B. Glocker*et al*

SinceThe authors address the issue of class imbalance affecting the accuracy of predictive models, particularly in image segmentation where neural networks may overfit to under-represented foreground samples. They identify a bias in logit activations at test time, causing a shift across the decision boundary for under-represented classes, leading to systematic under-segmentation of small structures. To mitigate this, the study introduces asymmetric variants of popular loss functions and regularization techniques, including large margin loss, focal loss, adversarial training, mixup, and data augmentation. Empirical evaluations across various segmentation tasks confirm that these modifications significantly enhance segmentation accuracy compared to conventional methods.

Q. Liu, G. Ma, and C. Cheng*et al*

As the study addresses the challenge of imbalanced class distributions in fault diagnosis of rotating machinery, which can compromise diagnostic accuracy using conventional machine learning algorithms due to uniform cost weights across fault classes. The research introduces a novel diagnostic framework leveraging adversarial neural networks (GAN) and multi-sensor data fusion to generate synthetic data for compensation. Two distinct practice modes, Pre-fusion GAN and Post-fusion GAN, are designed based on data fusion positioning logic. Without requiring data pre-processing, the framework generates synthetic data challenging the discriminator, effectively compensating for the minority class. Validated on two imbalanced datasets from rotating machinery, the proposed approach demonstrates superior performance compared to existing methods, showcasing its efficacy in imbalanced fault diagnosis

PROBLEM STATEMENT:

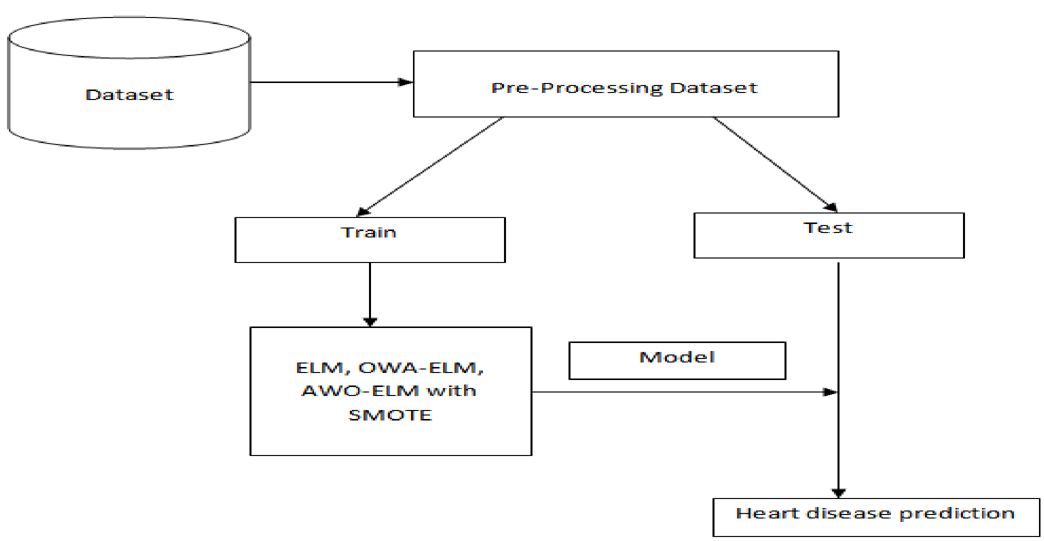
Extreme Learning Machine algorithm is deep learning algorithm which will filter data by using multiple neurons and this algorithm is using everywhere for classification such as Face recognition, health disease prediction and many more. This algorithm performance may go down while handling imbalance data (data which contains more instances in one CLASS and fewer instances in another CLASS which raise major and minor problem).

PROPOSED METHOD:

To overcome from above problem and to handle imbalance data with ELM author of this paper has enhance ELM by adding lesser BETA value. In ELM algorithm, beta is required as small as possible to avoid the structural risk of the model and resulting in weak generalization ability. However, if only slightly increase each element in the column vector that determines the output value of the minority output neuron in the output weight matrix Beta, it may not cause too much structural risk, but helps to improve the classification accuracy of minority class samples. So by enhancing beta value ELM performance can be increase and name as ‘output weight adjustment ELM’ (OWA-ELM).

In propose paper author has evaluate performance of OWA-ELM in terms of accuracy, precision, recall and FSCORE. Author has compare OWA-ELM with traditional ELM algorithm. To measure performance author has used 22 datasets and its bit difficult to use all those datasets so we have use Cleveland, PIMA and Wisconsin dataset.

ARCHITECTURE



DATASETS:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1
...	...	...	...	...	...	...	...	...	...
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

768 rows × 9 columns

Displaying PIMA dataset

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	...	t
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	...	
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	0.07017	...	
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	0.12790	...	
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	...	
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	...	
...	...	...	...	...	...	...	...	...	...	...	...	
564	926424	M	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	...	
565	926682	M	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	...	
566	926954	M	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	...	
567	927241	M	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	...	
568	92751	B	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	...	

569 rows × 33 columns

Displaying Wisconsin dataset

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	condition
0	69	1	0	160	234	1	2	131	0	0.1	1	1	0	0
1	69	0	0	140	239	0	0	151	0	1.8	0	2	0	0
2	66	0	0	150	226	0	0	114	0	2.6	2	0	0	0
3	65	1	0	138	282	1	2	174	0	1.4	1	1	0	1
4	64	1	0	110	211	0	2	144	1	1.8	1	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
292	40	1	3	152	223	0	0	181	0	0.0	0	0	2	1
293	39	1	3	118	219	0	0	140	0	1.2	1	0	2	1
294	35	1	3	120	198	0	0	130	1	1.6	1	0	2	1
295	35	0	3	138	183	0	0	182	0	1.4	0	0	0	0
296	35	1	3	126	282	0	2	156	1	0.0	0	0	2	1

297 rows × 14 columns

Displaying Cleveland dataset

METHODOLOGY:

1.1 Importing Required Python Packages:

The initial step involves importing essential libraries such as pandas, numpy, and scikit-learn. These libraries play a pivotal role in data manipulation, preprocessing, model evaluation, and visualization, facilitating streamlined development and analysis.

1.2 Reading and Displaying Datasets:

This project incorporates three distinct datasets: PIMA, Wisconsin, and Cleveland. These datasets encompass vital attributes including glucose levels, blood pressure, and age, which are instrumental in heart disease prediction. Data is loaded into pandas DataFrames, providing a comprehensive view of its structure and content.

1.3 Handling Missing Values:

Addressing missing values is crucial to maintain data integrity. In this project, missing values within the datasets are replaced with zeros, ensuring uniformity and facilitating subsequent processing steps.

1.4 Encoding Categorical Variables:

To facilitate model training, categorical variables within the datasets are encoded into numeric format. Label encoding techniques are employed to transform non-numeric data into numerical representations, ensuring compatibility with machine learning algorithms.

1.5 Feature Scaling:

To optimize model performance and prevent dominance by features with larger scales, Min-Max scaling is applied. This normalization technique ensures that all features contribute proportionally to model training, enhancing predictive accuracy.

1.6 Algorithm Selection:

Two distinct algorithms are implemented in this project: Existing Extreme Learning Machine (ELM) and Proposed OWA-ELM (Ordered Weighted Averaging Extreme Learning Machine). ELM is characterized by a single hidden layer neural network, while OWA-ELM incorporates an additional layer to address imbalanced data. Additionally, SMOTE (Synthetic Minority Over-sampling Technique) is applied to augment performance on imbalanced datasets.

1.7 Model Training and Evaluation:

The dataset is partitioned into training and testing subsets using a conventional split ratio. Both ELM and OWA-ELM models are trained on the training data and subsequently evaluated using a range of metrics including accuracy, precision, recall, and F1-score. Confusion matrices are generated to visualize the performance of these models in predicting diverse classes, with extension techniques like SMOTE employed to enhance model performance on imbalanced data.

1.8 Comparative Analysis:

A comprehensive comparative analysis is conducted to assess the performance of each algorithm across different datasets. Performance metrics, including accuracy, precision, recall, and F1-score, are calculated and juxtaposed to evaluate the efficacy of each algorithm in predicting heart disease.

1.9 Visualization:

To facilitate intuitive understanding and interpretation, bar graphs are plotted to visually depict the performance of each algorithm across various datasets. These graphical representations serve as valuable tools for assessing the comparative effectiveness and performance of the implemented algorithms.

1.10 Test Data Preparation:

Test data is subjected to similar preprocessing steps as the training data to ensure compatibility with the trained models, maintaining consistency and facilitating accurate predictions.

1.11 Prediction:

Utilizing the trained models, predictions regarding the likelihood of heart disease for the test data samples are made. Predictions are based on the highest probability class inferred from the models, providing valuable insights into potential heart disease risks.

EVOLUTION:

Precision:

Formula: $\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$

Code: precision = precision_score(testY, predict, average='macro') * 100

Recall (Sensitivity):

Formula: $\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$

Code: recall = recall_score(testY, predict, average='macro') * 100

F1 Score:

Formula: $F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$

Code: f1 = f1_score(testY, predict, average='macro') * 100

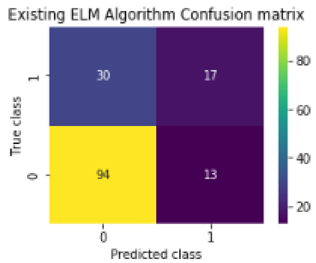
Accuracy:

Formula: $\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$

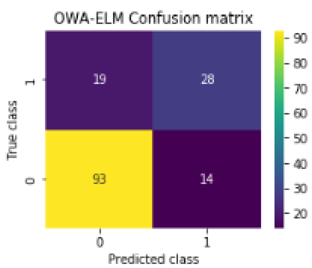
Code: accuracy = accuracy_score(testY, predict) * 100

RESULTS:

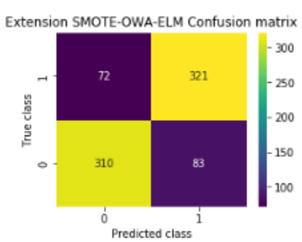
```
Dataset Name : Pima
Existing ELM Algorithm Accuracy  : 72.07792207792207
Existing ELM Algorithm Precision : 66.23655913978494
Existing ELM Algorithm Recall    : 62.01034002783854
Existing ELM Algorithm FMeasure  : 62.77056277056276
```




```
Dataset Name : Pima
OWA-ELM Accuracy  : 78.57142857142857
OWA-ELM Precision : 74.85119047619048
OWA-ELM Recall    : 73.24517796778683
OWA-ELM FMeasure  : 73.92642758196091
```

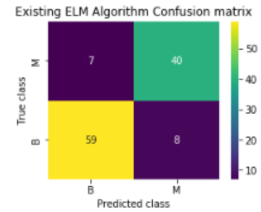



```
Dataset Name : Pima
Extension SMOTE-OWA-ELM Accuracy  : 80.27989821882952
Extension SMOTE-OWA-ELM Precision : 80.30363900264372
Extension SMOTE-OWA-ELM Recall    : 80.27989821882953
Extension SMOTE-OWA-ELM FMeasure  : 80.27603513174404
```

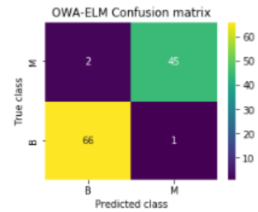


In above screen now train PIMA dataset with existing ELM, propose OWA-ELM and extension SMOTE-OWA-ELM and with existing ELM we got 72% accuracy and in confusion matrix graph x-axis represents PREDICTED labels and y-axis represents TRUE labels where yellow top blue colour boxes represents correct prediction count and other boxes represents incorrect prediction count. Propose OWA-ELM we got 78% accuracy and with extension we got 80% accuracy

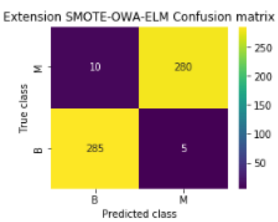
```
Dataset Name : Wisconsin
Existing ELM Algorithm Accuracy  : 86.8421052631579
Existing ELM Algorithm Precision : 86.36363636363636
Existing ELM Algorithm Recall    : 86.58304223563036
Existing ELM Algorithm FMeasure  : 86.46616541353383
```




```
Dataset Name : Wisconsin
OWA-ELM Accuracy  : 97.36842105263158
OWA-ELM Precision : 97.44245524296676
OWA-ELM Recall    : 97.12607176881549
OWA-ELM FMeasure  : 97.27598566308244
```

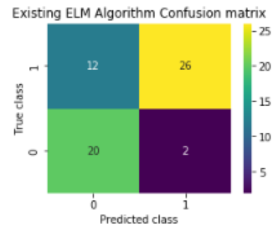



```
Dataset Name : Wisconsin
Extension SMOTE-OWA-ELM Accuracy  : 97.41379310344827
Extension SMOTE-OWA-ELM Precision : 97.42789176330658
Extension SMOTE-OWA-ELM Recall    : 97.41379310344827
Extension SMOTE-OWA-ELM FMeasure  : 97.41360089186175
```

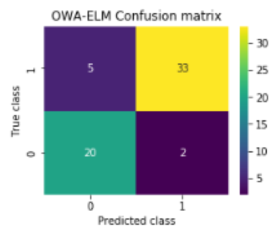


Training existing ELM with WISCONSIN dataset and we got 86% accuracy. With propose OWA-ELM on Wisconsin dataset we got 97.36% accuracy and with extension smote we got 97.41% accuracy

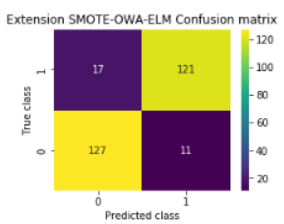
```
Dataset Name : Cleveland
Existing ELM Algorithm Accuracy  : 76.66666666666667
Existing ELM Algorithm Precision : 77.67857142857143
Existing ELM Algorithm Recall    : 79.66507177033493
Existing ELM Algorithm FMeasure  : 76.43097643097643
```



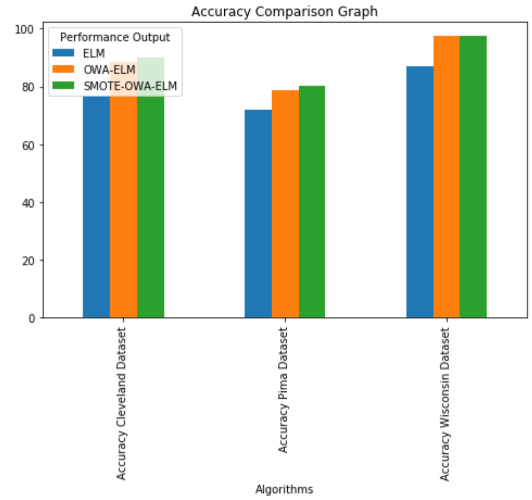

```
Dataset Name : Cleveland
OWA-ELM Accuracy  : 88.33333333333333
OWA-ELM Precision : 87.14285714285714
OWA-ELM Recall    : 88.8755980861244
OWA-ELM FMeasure  : 87.75867094141651
```



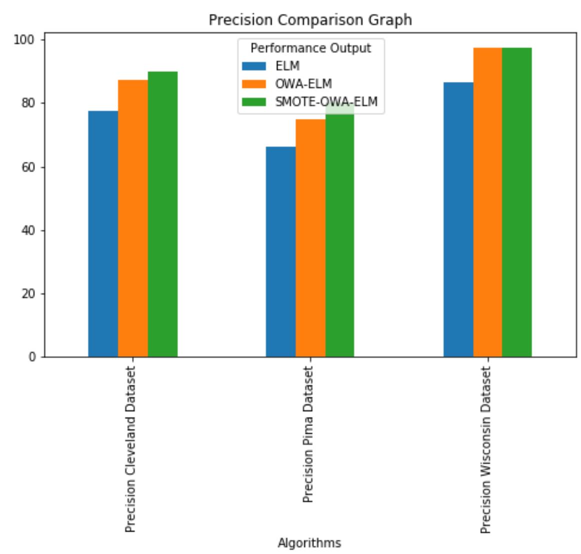

```
Dataset Name : Cleveland
Extension SMOTE-OWA-ELM Accuracy  : 89.85507246376811
Extension SMOTE-OWA-ELM Precision : 89.93055555555556
Extension SMOTE-OWA-ELM Recall    : 89.85507246376811
Extension SMOTE-OWA-ELM FMeasure  : 89.85027580772262
```



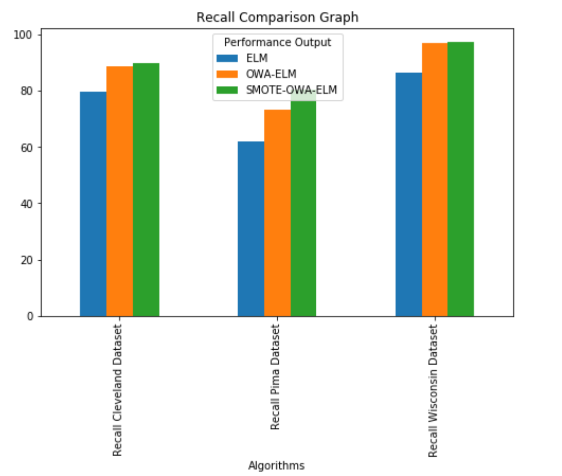
Training ELM with Cleveland dataset and got 76.66% accuracy. Propose OWA-Elm got 88% accuracy and extension got 89% accuracy



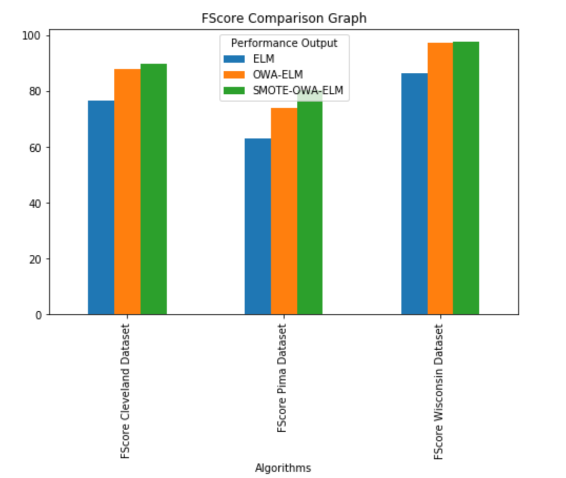
In above screen we can see accuracy graph of existing ELM, propose OWA-ELM and Extension SMOTE where x-axis represents algorithm names and y-axis represents accuracy and in all algorithms extension SMOTE got high accuracy



In above screen we can see precision graph of existing ELM, propose OWA-ELM and Extension SMOTE where x-axis represents algorithm names and y-axis represents Precision and in all algorithms extension SMOTE got high Precision



In above screen we can see recall graph of existing ELM, propose OWA-ELM and Extension SMOTE where x-axis represents algorithm names and y-axis represents recall and in all algorithms extension SMOTE got high recall



In above screen we can see FSCORE graph of existing ELM, propose OWA-ELM and Extension SMOTE where x-axis represents algorithm names and y-axis represents FSCORE and in all algorithms extension SMOTE got high FSCORE

	Dataset & Algorithm Name	Precison	Recall	FScore	Accuracy
0	ELM Pima Dataset	66.236559	62.010340	62.770563	72.077922
1	OWA-ELM Pima Dataset	74.851190	73.245178	73.926428	78.571429
2	Extension SMOTE-OWA-ELM Pima Dataset	80.303639	80.279898	80.276035	80.279898
3	ELM Wisconsin Dataset	86.363636	86.583042	86.466165	86.842105
4	OWA-ELM Wisconsin Dataset	97.442455	97.126072	97.275986	97.368421
5	Extension SMOTE-OWA-ELM Wisconsin Dataset	97.427892	97.413793	97.413601	97.413793
6	ELM Cleveland Dataset	77.678571	79.665072	76.430976	76.666667
7	OWA-ELM Cleveland Dataset	87.142857	88.875598	87.758671	88.333333
8	Extension SMOTE-OWA-ELM Cleveland Dataset	89.930556	89.855072	89.850276	89.855072

In above we can see all algorithms performance in tabular format for all datasets

Prediction:

```
[0, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1]
Test Data = [ 58.   0.   1. 136. 319.   1.   2. 152.   0.   0.   0.   2.   0.] ===> NO Heart Disease Detected
Test Data = [ 67.    1.    3.  160.  286.    0.    2.  108.    1.    1.5   1.    3.
   0. ] ===> Heart Disease Detected
Test Data = [ 67.    1.    3.  120.  229.    0.    2.  129.    1.    2.6   1.    2.
   2. ] ===> Heart Disease Detected
Test Data = [6.70e+01 1.00e+00 3.00e+00 1.25e+02 2.54e+02 1.00e+00 0.00e+00 1.63e+02
 0.00e+00 2.00e-01 1.00e+00 2.00e+00 2.00e+00] ===> Heart Disease Detected
Test Data = [ 56.   1.   1. 120. 240.   0.   0. 169.   0.   0.   2.   0.   0.] ===> NO Heart Disease Detected
Test Data = [ 56.    0.    1.  140.  294.    0.    2.  153.    0.    1.3   1.    0.
   0. ] ===> NO Heart Disease Detected
Test Data = [ 56.    1.    1.  120.  236.    0.    0.  178.    0.    0.8   0.    0.
   0. ] ===> NO Heart Disease Detected
Test Data = [ 70.    1.    3.  145.  174.    0.    0.  125.    1.    2.6   2.    0.
   2. ] ===> Heart Disease Detected
Test Data = [ 70.    1.    3.  130.  322.    0.    2.  109.    0.    2.4   1.    3.
   0. ] ===> Heart Disease Detected
Test Data = [ 68.    1.    3.  144.  193.    1.    0.  141.    0.    3.4   1.    2.
   2. ] ===> Heart Disease Detected
Test Data = [ 67.    1.    3.  100.  299.    0.    2.  125.    1.    0.9   1.    2.
   0. ] ===> Heart Disease Detected
```

In above screen we are performing prediction on test data and in square bracket we can see test data and after arrow symbol =➔ we can see classification output as ‘No heart disease detected’ or ‘Heart disease detected’

CONCLUSION

This project focuses on enhancing the Extreme Learning Machine (ELM) algorithm, crucial for various classifications like face recognition and health disease prediction. ELM's performance falters with imbalanced data, posing major and minor problems. To address this, the author enhances ELM by adjusting the beta value, resulting in 'Output Weight Adjustment ELM' (OWA-ELM). By slightly increasing beta, the classification accuracy of minority class samples improves without significant structural risk. OWA-ELM's performance is evaluated against traditional ELM using datasets like Cleveland, PIMA, and Wisconsin. As an extension, OWA-ELM is combined with the deep learning SMOTE algorithm, boosting FSCORE significantly compared to other algorithms, providing a robust solution to data imbalance.

REFERENCES:

[1] S. Dhar and V. Cherkassky, ‘‘Development and evaluation of cost-sensitive Universum-SVM,’’ IEEE Trans. Cybern., vol. 45, no. 4, pp. 806–818, Apr. 2015.

[2] A. Teng, L. Peng, Y. Xie, H. Zhang, and Z. Chen, ‘‘Gradient descent evolved imbalanced data gravitation classification with an application on internet video traffic identification,’’ Inf. Sci., vol. 539, pp. 447–460, Oct. 2020.

[3] Z. Li, K. Kamnitsas, and B. Glocker, ‘‘Analyzing overfitting under class imbalance in neural networks for image segmentation,’’ IEEE Trans. Med. Imag., vol. 40, no. 3, pp. 1065–1077, Mar. 2021.

[4] C. Huang, X. Huang, Y. Fang, J. Xu, Y. Qu, P. Zhai, L. Fan, H. Yin, Y. Xu, and J. Li, ‘‘Sample imbalance disease classification model based on association rule feature selection,’’ Pattern Recognit. Lett., vol. 133, pp. 280–286, May 2020.

[5] C. V. Priscilla and D. P. Prabha, ‘‘Influence of optimizing XGBoost to handle class imbalance in credit card fraud detection,’’ in Proc. 3rd Int. Conf. Smart Syst. Inventive Technol. (ICSSIT), Aug. 2020, pp. 1309–1315.

[6] Q. Liu, G. Ma, and C. Cheng, ‘‘Data fusion generative adversarial network for multi-class imbalanced fault diagnosis of rotating machinery,’’ IEEE Access, vol. 8, pp. 70111–70124, 2020.

[7] N. Tomašev and D. Mladenić, ‘‘Class imbalance and the curse of minority hubs,’’ Knowl.-Based Syst., vol. 53, pp. 157–172, Nov. 2013.

[8] Z. Xu, D. Shen, T. Nie, and Y. Kou, ‘‘A hybrid sampling algorithm combining M-SMOTE and ENN based on random forest for medical imbalanced data,’’ J. Biomed. Informat., vol. 107, Jul. 2020, Art. no. 103465.

[9] G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew, ‘‘Extreme learning machine: Theory and applications,’’ Neurocomputing, vol. 70, nos. 1–3, pp. 489–501, 2006.

[10] G. B. Huang, H. Zhou, X. Ding, and R. Zhang, ‘‘Extreme learning machine for regression and multiclass classification,’’ IEEE Trans. Syst., Man, Cybern., B, Cybern., vol. 42, no. 2, pp. 513–524, Apr. 2012.

[11] B. Ahuja and V. P. Vishwakarma, ''Local feature extraction based KELM for face recognition,'' in Proc. 12th Int. Conf. Contemp. Comput. (IC3), Aug. 2019, pp. 1–5.

[12] K. Rujirakul and C. So-In, ''Histogram equalized deep PCA with ELM classification for expressive face recognition,'' in Proc. Int. Workshop Adv. Image Technol. (IWAIT), Jan. 2018, pp. 1–4.

[13] X. Ximeng, Y. Rennong, and Y. Yang, ''Threat assessment in air combat based on ELM neural network,'' in Proc. IEEE Int. Conf. Artif. Intell. Comput. Appl. (ICAICA), Mar. 2019, pp. 114–120.

[14] F. Huang, J. Lu, J. Tao, L. Li, X. Tan, and P. Liu, ''Research on optimization methods of ELM classification algorithm for hyperspectral remote sensing images,'' IEEE Access, vol. 7, pp. 108070–108089, 2019.

[15] L. Li, J. Zeng, L. Jiao, P. Liang, F. Liu, and S. Yang, ''Online active extreme learning machine with discrepancy sampling for PolSAR classification,'' IEEE Trans. Geosci. Remote Sens., vol. 58, no. 3, pp. 2027–2041, Mar. 2020.

[16] M. Sharifmoghadam and H. Jazayeriy, ''Breast cancer classification using AdaBoost-extreme learning machine,'' in Proc. 5th Iranian Conf. Signal Process. Intell. Syst. (ICSPIS), Dec. 2019, pp. 1–5.

[17] S. Saxena, S. Shukla, and M. Gyanchandani, ''Breast cancer histopathology image classification using kernelized weighted extreme learning machine,'' Int. J. Imag. Syst. Technol., vol. 31, no. 1, pp. 168–179, Mar. 2021.

[18] K. Li, X. Kong, Z. Lu, L. Wenyin, and J. Yin, ''Boosting weighted elm for imbalanced learning,'' Neurocomputing, vol. 128, pp. 15–21, Mar. 2014.

[19] W. Zong, G.-B. Huang, and L. Chen, ''Weighted extreme learning machine for imbalance learning,'' Neurocomputing, vol. 101, pp. 229–242, Feb. 2013.

[20] H. Yu, C. Sun, X. Yang, S. Zheng, Q. Wang, and X. Xi, ''LW-ELM: A fast and flexible cost-sensitive learning framework for classifying imbalanced data,'' IEEE Access, vol. 6, pp. 28488–28500, 2018.