

## Improving the Efficacy of Adaptive Boosting Classifiers by Dynamic Weight Adjustment

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### Abstract:

The AdaBoost algorithm has proven robust performance across many classification possibilities. However, its applicability in real-time is frequently restricted by its susceptibility to noisy, imbalanced, and high-dimensional data. This study proposed a Dynamic Weight Adjustment AdaBoost (DWA-AdaBoost) to improve AdaBoost's classification efficiency in such scenarios. The approach dynamically adjusted sample weights based on classification difficulty and an estimation of local noise. It integrated a noise-sensitivity element into the weight adjustment process, enabling the system to dynamically decrease the impact of noisy or misclassified instances. The methodology included performance measurements and computational efficiency using MATLAB simulation after cleaning, processing all datasets, and utilizing a 5-fold cross-validation approach to provide a more dependable evaluation of the performance of the models. The method's effectiveness was assessed using three real-world datasets: Spambase, Wine Quality, and Diabetes. Empirical evaluations showed that DWA-AdaBoost continually surpassed standard AdaBoost across many essential performance metrics. On the Spambase dataset, the model achieved gains of 3.04% accuracy, 4.85% precision, and 3.89% F1-score. On the Wine Quality data, the model achieved gains of 2.4% accuracy, 1.19% precision, and 0.63% F1-score. The results demonstrated the algorithm's resilience to noise and fast convergence, emphasizing its suitability for real-time predictive analytics in spam detection, healthcare diagnostics, and quality control applications.

**Keywords:** AdaBoost, DWA-AdaBoost, Real-time application, Spambase, Diabetes prediction, Wine quality

### 1. Introduction

Ensemble learning has become a crucial method in machine learning, enhancing generalization and robustness through the integration of many weak learners [1]. Among ensemble approaches, AdaBoost has received considerable interest due to its advanced formulation and demonstrated efficacy across classification problems [2]. AdaBoost performs by continuously training weak learners and modifying the weighting of samples, therefore emphasizing situations that are difficult to categorize [3]. Despite its efficacy, AdaBoost is constrained by several restrictions, particularly in the context of imbalanced, noisy datasets. A primary limitation of the AdaBoost model involves the static weight adjustment method, which elevates the weighting of misclassified instances with no regard for the complexity of the data [4].

This method results in the model overfitting outliers or noise in minority classes, thereby reducing the generalization performance. In practical situations, the inflexibility in weight distribution decreases AdaBoost's efficacy and scalability [5]. This study presents an innovative improvement to the AdaBoost construction by integrating a Dynamic Weight Adjustment strategy (DWA) to tackle these problems. The method utilizes an update technique that adaptively adjusts the relative weights

of the training data according to an analysis of error structures, previous learning trends [6]. Enabling the model to distinguish between genuinely informative errors and deceptive noise. The approach aims to enhance precision and resilience by adjusting to the changing learning environment. The DWA technique improves the model's stability, interpretability, and convergence speed, making it more suitable for real-time applications [7].

This study presents a novel enhancement to the conventional AdaBoost method through the integration of a Dynamic weight adjustment technique aimed at improving the classifier's adaptation and robustness in complex and noisy situations. A comprehensive assessment utilizing benchmark real-time datasets from fields such as healthcare, quality control, and spam identification reveals enhancements in accuracy, recall, and F1-score relative to traditional AdaBoost. Additionally, an in-depth analysis of model performance under varying noise levels and data imbalance conditions substantiates DWA-AdaBoost's superior generalization capabilities.

## 2. Literature Review

Recent ensemble learning advancements have improved the AdaBoost model's applicability. Many study initiatives focused on including Dynamic Weight Adjustment techniques into the AdaBoost methodology, resulting in enhancements in real-time performance [8]. Ding et al. (2022) introduced a multi-threshold AdaBoost with weak learning abilities to assess multiple decision thresholds. This method is supplemented by an updated weighting methodology emphasizing instances with the highest classification errors over thresholds. Experimental evaluation shows that the proposed approach exceeds the AdaBoost model in classification accuracy and generalization capabilities [9].

Ahmed and Liu (2024) presented an error-proportional weighting method within the AdaBoost which instance weights are adjusted according to the magnitude of prediction mistakes. Practical evaluations across many datasets reveal a 2% increase in accuracy, accompanied by improved F1-scores, mainly under class-imbalanced and noisy situations [10]. Li et al. (2024) proposed a dynamic weighting technique for AdaBoost that includes a Misclassification Difference Index (MCDI) to enhance the instance weighting process by adjusting weights on misclassification. Empirical findings from geoscientific datasets indicate an approximate 2.3% improvement in predicting accuracy. These findings underscored the effectiveness of MCDI weighting in enhancing the equity and robustness of the approach [11].

Song et al. (2024) developed a fairness modification of the AdaBoost model by integrating a dynamic reweighting approach to reduce prediction bias among demographic categories. Using instance weights to rectify imbalances in model performance, empirical evaluations conducted on healthcare databases indicate that the method maintains good accuracy and has the potential to enhance the proposed method enhancing clinical consistency in medical programs [12]. Chen and Zhao (2025) proposed an asynchronous AdaBoost suited for mutual instruction, combining delayed weight and asynchronous update methodologies to address the distributed characteristics of data and enhance computational efficiency. Experimental results across various datasets demonstrate a significant reduction in training time (20–35%). When applied asynchronously, it develops communication scalability in remote environments [13].

Xie et al. (2025) developed GAdaBoost, an innovative ensemble learning service that granular-ball generation to preprocess training data by modifying redundant instances and the influence of noise, which is used to regulate instance weights dynamically through the boosting procedure. Practical evaluations on datasets with variable noise levels establish that GAdaBoost improves computational efficiency and robustness compared to standard boosting methods [14]. This study indicates that DWA-AdaBoost can improve AdaBoost's robustness, scalability, and accuracy, especially under real-time restrictions, noise, and imbalanced class populations. Its performance suggests its broad use in real-world predictive applications.

### 3. Methodology

The proposed DWA-AdaBoost approach presents an advanced ensemble learning algorithm that enhances the AdaBoost by incorporating a dynamic weight update procedure to improve classification quality in situations involving real-time, imbalanced, and noisy data [15]. All tests were executed in the MATLAB R2023a program with simultaneous processing, using a 5-fold cross-validation approach to ensure the model's generalizability and reliability [16]. The methodology comprises fundamental elements, as shown:

#### 3.1 Dataset Description and Processing

This study utilized three real-world datasets of varying sizes for analysis and model assessment. The Spambase dataset consists of 4,601 email samples, each defined by 57 continuous attributes, and is classified into spam and non-spam categories. The dataset is moderately-sized and exhibits a moderate noise level. However, it is considered moderately balanced, with a relatively even distribution of spam and non-spam instances [17]. The Wine quality dataset comprises 4,898 biophysical measures of white wines, accompanied by quality scores from 0 to 10 for the binary classification. The dataset is imbalanced, with most data classified as intermediate quality. It shows moderate noise due to the nature of the quality and distinctions in measurement [18]. The diabetes health indicators dataset comprises 15,000 patient records, encompassing 21 unique variables, including behavioral, physiological, and demographic medical data. The target indicates the diabetes (1) or no diabetes (0). The dataset represents a large-scale, real-world collection considered by class imbalance and substantial noise [19]. All three datasets underwent a comprehensive preparation protocol to ensure uniformity and suitability for modeling [20]. Missing values were addressed by median imputation for numerical characteristics, while variable categories, when relevant, were converted using label encoding. All numerical properties were standardized by z-score normalization.

$$x^* = \frac{x - \mu}{\sigma} \quad (1)$$

When ( $x$ ) is the original feature value, ( $\sigma$ ) the standard deviation of the feature, and ( $\mu$ ) is the mean value. The dataset is divided into training subsets (80%) and testing (20%) using a stratified split to maintain the original class distribution in both the training and testing sets.

#### 3.2 DWA-AdaBoost algorithm

The DWA-AdaBoost techniques improve on the standard AdaBoost methodology by including an adaptive procedure that considers the noise content of particular samples throughout the boosting process [21]. Standard AdaBoost modifies the weight of each training instance solely based on misclassification, which may lead to overfitting noisy or confusing data. DWA-AdaBoost enhances this method by incorporating a noise-awareness element into the weighting update estimation as the updated weight for instance, is computed as:

$$w_i^{(t+1)} = w_i^{(t)} \cdot \exp(-\alpha_t y_i h_t(x_i) + \delta_t) \quad (2)$$

$$\delta_t = \lambda \cdot \frac{\epsilon_t - \epsilon_t^*}{\epsilon_t} \quad (3)$$

#### Algorithm-1 AdaBoost Model

##### Input:

Train dataset  $\mathcal{D} = \{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$ , with  $x_i \in \mathbb{R}^d$ ,  $y_i \in \{0, 1\}$  of binary classification.

$x_i$ : Input features for the  $i$  sample.

$y_i$ : Target label for the  $i$  sample.

$N$ : Number of samples.

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**Procedure:**

Weights are initialized:

$$w_1(i) = \frac{1}{N}, \quad \text{for } i = 1, 2, \dots, N$$

For  $t = 1$  to  $T$ .

Weak learners are trained  $h_t(x)$  for distribution  $w_t$ , and weighted error ( $\varepsilon_t$ ) is calculated,

$$\varepsilon_t = \sum_{i=1}^N w_t(i) \cdot I(h_t(x_i) \neq y_i)$$

$I(\cdot)$ : Indicator function, equal to (1) if  $h_t(x_i) \neq y_i$ , and (0) otherwise.

$h_t(x)$ : The weak learner at iteration  $t$ .

Then, the model weight ( $\alpha_t$ ) is computed,

$$\alpha_t = \frac{1}{2} \ln \left( \frac{1 - \varepsilon_t}{\varepsilon_t} \right)$$

Weights  $w_{t+1}(i)$  are updated,

$$w_{t+1}(i) = w_t(i) \cdot \exp(-\alpha_t y_i h_t(x_i))$$

$y_i h_t(x_i)$ : Equals (1) for correct predictions and (0) for incorrect predictions.

Weights are normalizing:

$$w_{t+1}(i) = \frac{w_{t+1}(i)}{\sum_{j=1}^N w_{t+1}(j)}$$

End For.

**Output:**

Final strong classifier,

$$H(x) = \text{sign} \left( \sum_{t=1}^T \alpha_t h_t(x) \right)$$

$\text{sign}(\cdot)$  returns (1) if the argument is positive and (0) otherwise [22].

**Algorithm-2 DWA- AdaBoost Model**

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**Input:**

Train dataset  $\mathcal{D} = \{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$ , with  $x_i \in \mathbb{R}^d$ ,  $y_i \in \{0, 1\}$  for binary classification.

**Procedure:**

Weights initialized:

$$w_1(i) = \frac{1}{N}$$

The weighted error ( $\varepsilon_t$ ) is calculated, for  $t=1$  to  $T$ .

$$\varepsilon_t = \sum_{i=1}^N w_t(i) \cdot I(h_t(x_i) \neq y_i)$$

The classifier weight ( $\alpha_t$ ) is computed,

$$\alpha_t = \frac{1}{2} \ln \left( \frac{1 - \epsilon_t}{\epsilon_t} \right)$$

The dynamic adjustment term ( $\delta_t$ ) is calculated,

$$\delta_t = \lambda \cdot \frac{\epsilon_t - \epsilon_t^*}{\epsilon_t}$$

$\lambda$ : is the dynamic coefficient associated with noise estimation and  $\epsilon_t^*$ : is the average error up to iteration  $t$ .

the weights  $w_i^{(t+1)}$  are updated:

$$w_i^{(t+1)} = w_i^{(t)} \cdot \exp(-\alpha_t y_i h_t(x_i) + \delta_t)$$

This weight is an essential factor in ( $\epsilon_t$ ) that is, the effect on computed classifier weight ( $\alpha_t$ ).

The weights are normalized,

$$w_i^{(t+1)} = \frac{w_i^{(t+1)}}{\sum_{j=1}^N w_j^{(t+1)}}$$

### Output:

The final strong classifier [23],

$$H(x) = \text{sign} \left( \sum_{t=1}^T \alpha_t h_t(x) \right)$$

The dynamic weight adjustment approach significantly improves the AdaBoost model by enhancing robustness against outliers and optimizing real-time classification [24]. This technique allows us to develop more adaptable, reliable, and effective systems across various domains.

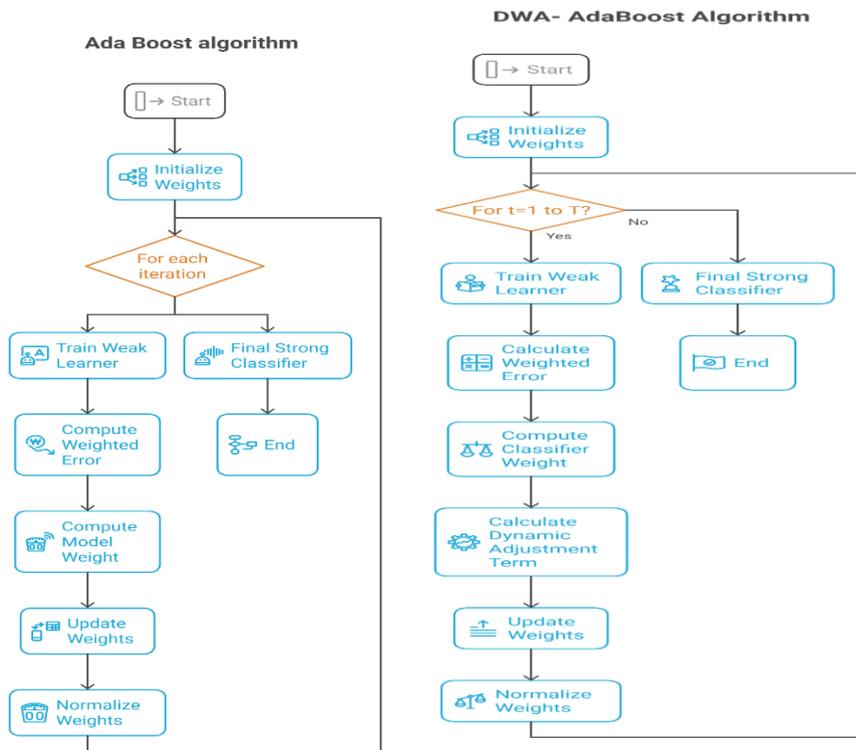


Fig.1 AdaBoost and DWA-AdaBoost flowcharts.

### 3.3 Evaluation Model

The performance of the AdaBoost and DWA-AdaBoost models was evaluated using several metrics, including accuracy, precision, recall, F1-score, Area Under the ROC Curve (AUC), and training/testing time [25]. These metrics are derived from the confusion matrix components: True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN).

#### 1) Accuracy

The proportion of correctly classified instances to the total cases. It delivers a general valuation of a model's quality by assessing the proportion of correct predictions.

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad (4)$$

#### 2) Precision

Measures the proportion of correctly positive to all positive predictions the model makes. It is crucial when false positives are costly.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (5)$$

#### 3) Recall

Evaluates the model's accuracy in detecting all real positive predictions. This is the highest priority for states with strict penalties for false negative cases.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (6)$$

#### 4) F1-Score

The harmonic average of precision and recall offers an integrated metric that equilibrates them. It is constructive for situations where class proportions are unequal.

$$\text{F1 - Score} = \frac{2 \times (\text{Prec} \times \text{Rec})}{\text{Prec} + \text{Rec}} \quad (7)$$

#### 5) ROC-Curve

The curve represents the relationship between the false positive rate (FPR) and the actual positive rate (TPR) across different threshold stages. It measures the model's capacity to differentiate between classes. A high value indicates the model's efficacy in identifying positive and negative classes [26].

### 4. Result analysis simulation

This section presents a comparative performance assessment between DWA-AdaBoost classifiers and other models using three datasets: Spambase, Wine Quality, and Diabetes. The evaluation covers both classification performance and computational efficiency. To ensure a reliable evaluation of the models' performance, key metrics including accuracy, precision, recall, F1-score, AUC, and training/testing times were calculated. All experiments were conducted in MATLAB R2023a and followed a comprehensive protocol that included data cleaning, preprocessing, and a 5-fold cross-validation procedure.

#### 4.1 Classification Efficacy

DWA-AdaBoost consistently performed superior to the standard AdaBoost, XGBoost, Rf for all datasets, particularly in predictive accuracy, F1-score, precision, and ROC-curve. The results indicate improvement in classification metrics, thereby enhancing the reliability of classification performance as in Table 1.

Table 1: The models' performance.

Dataset	Model	Accuracy	Precision	Recall	F1-score	ROC
Spambase	AdaBoost	90.07	89.70	84.56	87.03	0.94
	DWA-AdaBoost	93.11	94.55	87.59	90.92	0.97
	XGBoost	91.04	90.99	92.43	91.75	0.95
	RF	90.65	89.63	91.76	90.17	0.93
Wine-white	AdaBoost	77.56	80.44	85.69	82.98	0.82
	DWA-AdaBoost	79.96	81.63	85.69	83.61	0.83
	XGBoost	77.89	76.78	78.24	77.51	0.82
	RF	75.74	74.42	76.63	75.55	0.79
Diabetes	AdaBoost	73.05	71.60	77.34	74.85	0.80
	DWA-AdaBoost	73.58	72.28	78.32	75.17	0.81
	XGBoost	72.98	71.64	73.37	72.52	0.79
	RF	71.48	70.69	73.32	72.02	0.78

When the confusion matrix of the AdaBoost and DWA-AdaBoost algorithms is shown in the figures below:

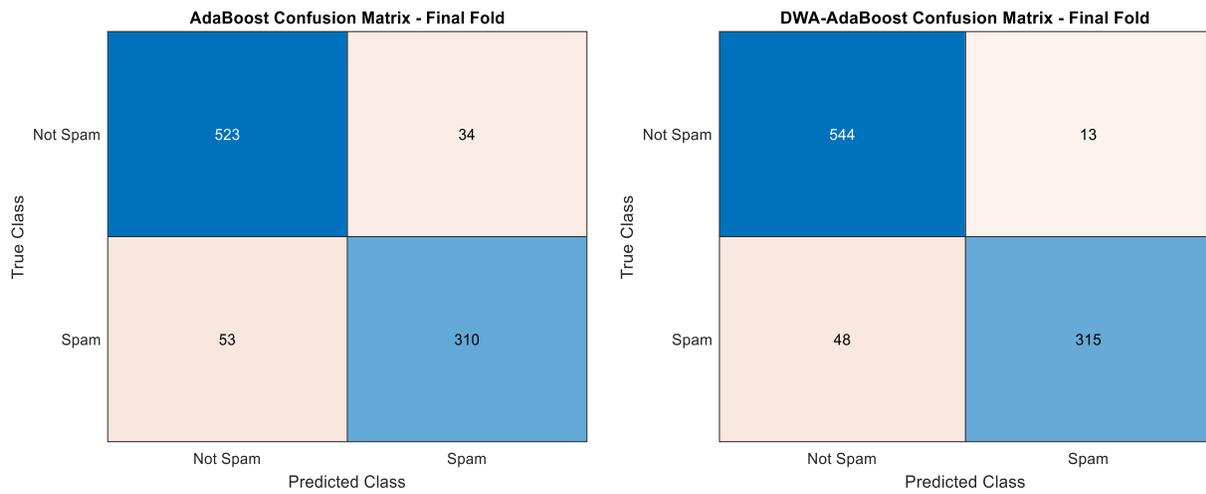


Fig. 2 Confusion matrix for the spambase dataset.

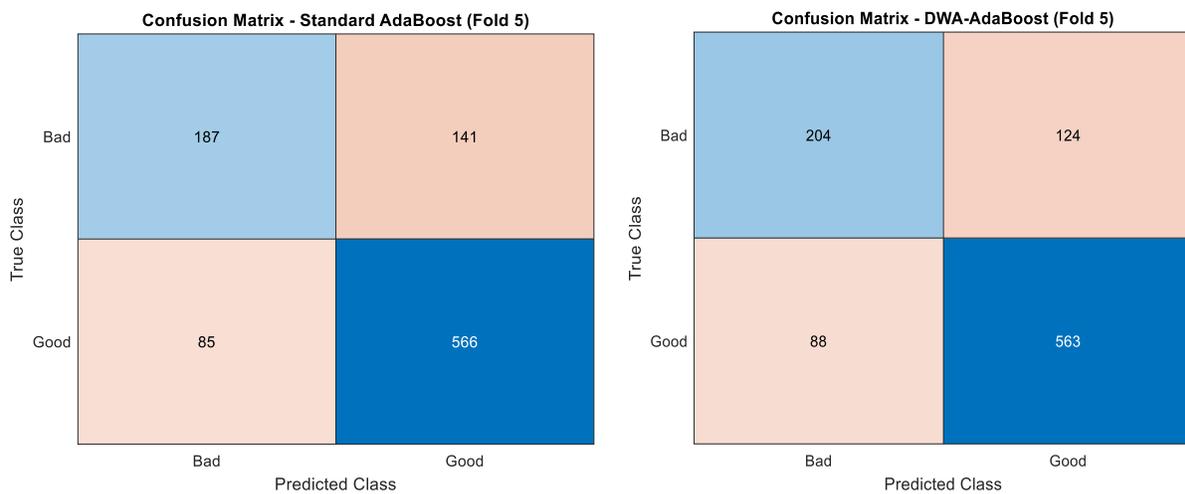


Fig.3 Confusion matrix for wine quality dataset.

## 4.2 ROC- Curve

The ROC curves for all data sets demonstrate the better performance of DWA-AdaBoost, with Area under the curve (AUC) results exceeding those of AdaBoost. Underscores DWA-AdaBoost's superior capacity to differentiate across classes, particularly in datasets characterized by noisy borders, such as the Spam base dataset.

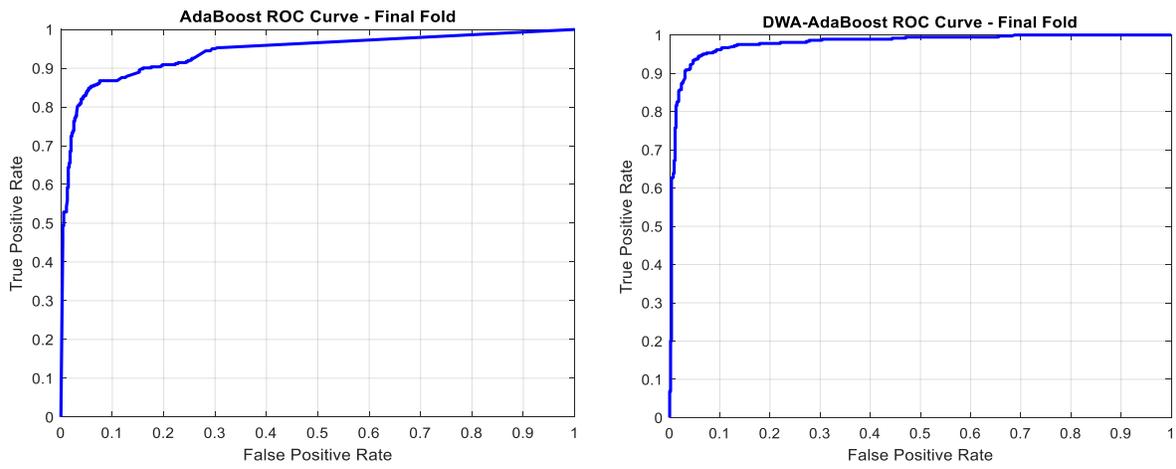


Fig.4 ROC-curve of the spambase dataset.

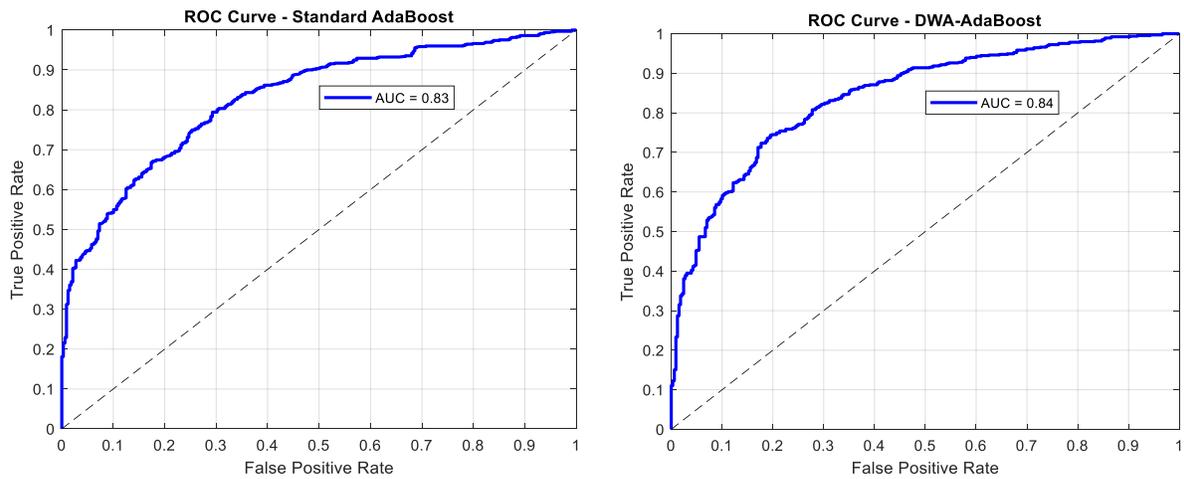


Fig. 5 ROC-curve of wine quality dataset.

### 4.3 Execution Time analysis

To evaluate the real-time applicability of the algorithms, their training and testing times were measured. While DWA-AdaBoost incorporates additional computational steps for dynamic noise estimation, it benefits from a more stable learning procedure, which can lead to faster convergence in boosting iterations [27]. By converging in fewer iterations, the approach can achieve high efficacy while potentially reducing the overall training time. The measured execution times for both models are presented in Table 2

Table 2: Train and test times of all models.

Dataset	Model	Train time(s)	Test time(s)
<b>Spambase</b>	AdaBoost	1.02	0.02
	DWA-AdaBoost	0.90	0.018
	XGBoost	1.1	0.04
	RF	0.96	0.03
<b>Wine quality</b>	AdaBoost	0.30	0.02
	DWA-AdaBoost	0.23	0.005
	XGBoost	0.5	0.03
	RF	0.4	0.02
<b>Diabetes</b>	AdaBoost	0.29	0.03
	DWA-AdaBoost	0.53	0.02
	XGBoost	0.56	0.05
	RF	0.35	0.04

#### 4.4 Result Analysis

The empirical evaluation illustrates a performance analysis of standard AdaBoost and the enhanced DWA-AdaBoost algorithm over 100 boosting iterations, emphasizing classification accuracy. DWA-AdaBoost exhibits significantly improved convergence relative to the AdaBoost model. This fast convergence underscores DWA-AdaBoost's enhanced capacity to adaptively prioritize difficult-to-classify instances and reduce the influence of noisy data. Additionally, DWA-AdaBoost demonstrates superior overall accuracy, which signifies enhanced resilience and generalization capacity [28]. However, normal AdaBoost exhibits considerable variability and decreased accuracy, probably because of consistent weight adjustment that may significantly amplify noise.

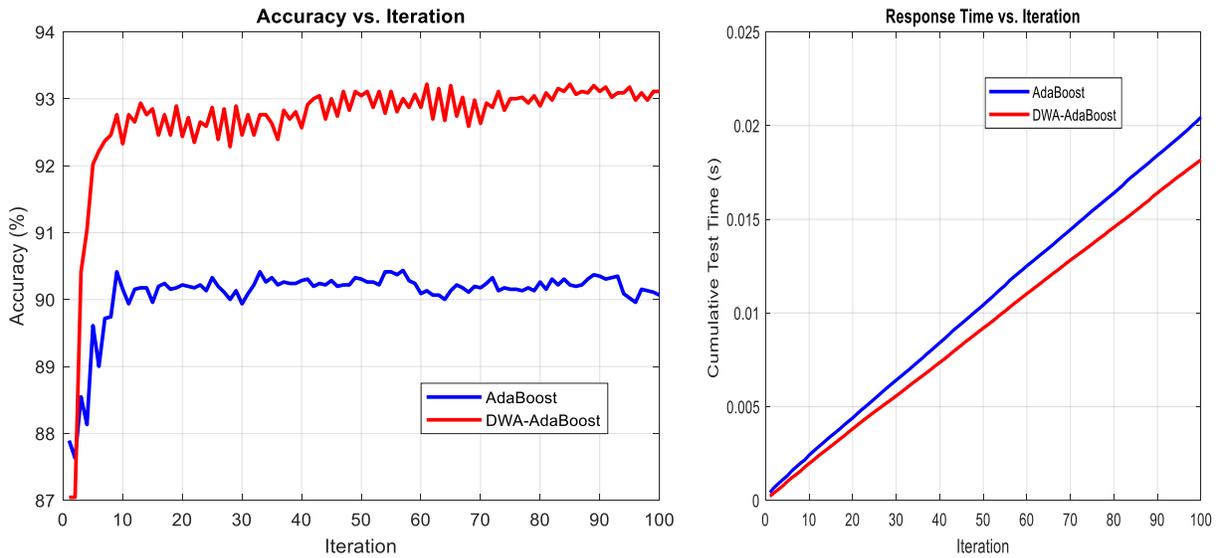


Fig.6 Accuracy and response time curves on spambase dataset.

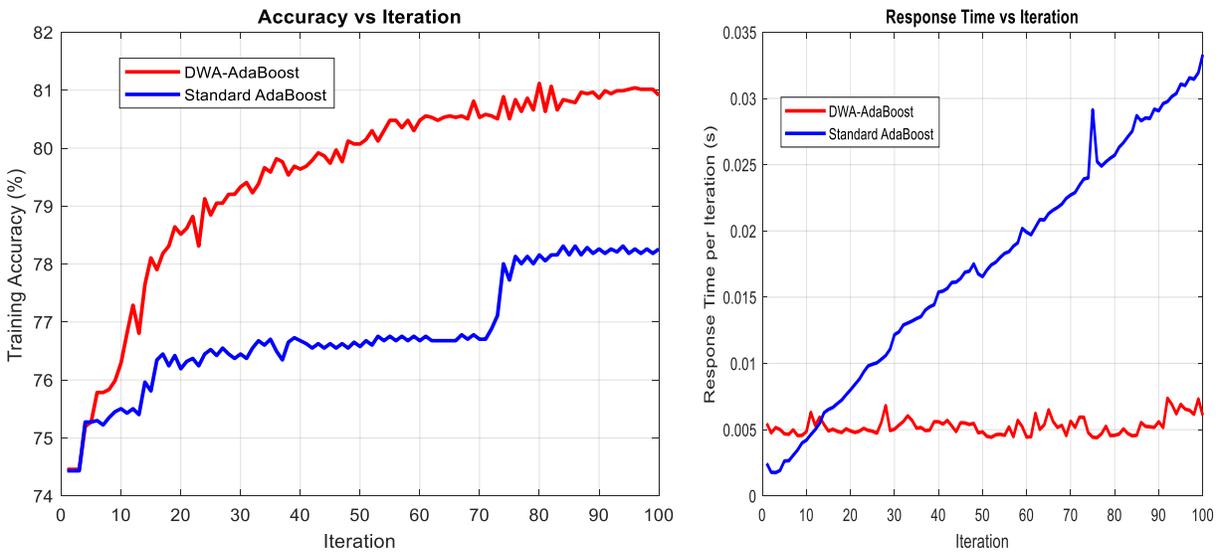


Fig.7 Accuracy and response time curves on wine quality dataset.

## 5. Conclusions

This study introduced an improved AdaBoost model (DWA-AdaBoost) version to enhance real-time classification efficacy. The practical analysis performed on three datasets, wine quality, spam base, and diabetes, revealed that DWA-AdaBoost improves the AdaBoost classifier regarding accuracy, F1-score, and ROC. The proposed DWA-AdaBoost technique exhibits significant improvements on the Spambase dataset and modest to marginal improvements on the Wine Quality and Diabetes datasets, suggesting its potential effectiveness is context-dependent. It achieves superior noise-handling capabilities, faster convergence, and superior classification performance. These advancements confirm its suitability for real-time applications in various domains, including email detection, wine quality, and healthcare diagnostics. Demonstrates that DWA-AdaBoost is a powerful and effective boosting method for real-time applications. Future research may investigate the combination of DWA-AdaBoost with deep ensemble designs and adaptive noise detection techniques to enhance its usefulness in extensive, real-world situations.

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