

Adaptive Fuzziness Weighting for Dynamic Instance Replication and Improved Classifier Generalization

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ABSTRACT

Classification performance often degrades when training datasets include noisy and ambiguous instances that are near class decision boundaries. Conventional instance selection and weighting methods use predefined rules or error measures that fail to leverage the instance uncertainty. To address these limitations, this study proposed the Adaptive Fuzziness Weighting (AFW) framework, which dynamically learns instance uncertainty and uses it to replicate training instances to enhance classifier generalization. The proposed method involves three stages: Estimating fuzziness for each training instance by utilizing posterior probabilities provided by a Neural Network with Random Weights (NNRw). Learning an adaptive mapping from instance fuzziness to instance replication weight using a Ridge Regression meta-learner. Fuzziness Guided Instance Replication (FGIR) is applied in order to resample the training distribution in anticipation of retraining. The framework has been evaluated on 10 different UCI datasets ranging across application, size, and difficulty using 10-fold cross-validation. The AFW framework consistently outperforms the baseline NNRw, increasing average classification accuracy from 0.7134 to 0.9266. The classification accuracy improves by 21.32% and 29.88% in absolute and relative terms over the entire dataset, respectively. The results suggest that adaptive exploitation of instance fuzziness is an effective approach to strengthen decision boundary learning, leading to improved classifier generalization. The AFW framework provides a practical, uncertainty-aware, and data-driven methodology to boost classifier generalization.

Keywords: Adaptive Fuzziness Weighting, Meta-Learning Framework, Instance Fuzziness, Ridge Regression, Dynamic Instance Replication, Generalization Accuracy

1. INTRODUCTION

Machine Learning (ML) classifiers have become an integral part of any intelligent decision-support system and are widely used in healthcare, finance, cyber-security, bio-informatics, and pattern recognition domains[1, 2]. Their ability to accurately learn the decision boundary is essential for generalization to unseen data. However, the classifier's performance is severely affected when there are ambiguity instances present in the training dataset that lie in the neighborhood of class decision boundaries. Such ambiguity instances have higher uncertainty as they resemble more than one class simultaneously and become hard to classify consistently [3, 4]. Though ambiguity instances are often perceived as noise or unreliable samples, these instances carry structural information of class separability. Failure to use or learn from ambiguity instances could lead to unstable decision boundaries, poor classification performance and lack of generalization [5, 6]. Many approaches like instance selection, sample weighting, data resampling, and uncertainty-based learning has been studied to make the classifier more robust [7, 8]. Traditional instance selection attempts to remove non-informative or noisy samples and to simplify the learning process whereas data oversampling addresses class imbalance by over-representing minority class samples. The use of adaptive sample weighting and meta learning approaches has also been explored for giving varying degrees of importance to the training instances based on their contributions to the learning objectives[2, 8]. Similarly, uncertainty-aware learning is a growing trend in which the prediction confidence and certainty information is employed to improve classifier robustness [5, 6, 9]. Most of these methods, however, rely on heuristics, predetermined fixed thresholds or error driven weights and do not explicitly learn how instance uncertainty should influence the learning process. Hence, they are generally not adaptable for datasets with different levels of uncertainty and complexity [6, 8]. The study [10] used the fuzziness of an instance to guide the instance selection within a Divide-and-Conquer (D&C) framework. Their approach established that not all ambiguous boundary instances need to be removed, but that they could be intelligently classified and used to enhance the performance. The fuzziness was proposed as a measure of importance and showed it could improve classification

accuracy. However, the fuzziness categories were defined using predetermined thresholds which remain fixed across all datasets and thus lack adaptivity with varying data distribution and boundary complexity[10]. In addition, the existing fuzziness-based methods do not often utilize an automatically learning approach for translating fuzziness to its importance during training [11, 12].

In order to mitigate these limitations, the study proposed an Adaptive Fuzziness Weighting (AFW) framework which dynamically learns the contribution of each training instance by learning the relation between instance fuzziness and instance replication weight through a lightweight Ridge Regression meta-learner [13, 14]. The proposed AFW consists of three stages. In the first stage, fuzziness for each training sample is estimated from posterior probability distributions predicted by a Neural Network with Random Weights (NNRw)[1]. In the second stage, an adaptive function for the relationship between instance fuzziness and its replication weight is learned using the meta-learner. In the final stage, an information rich boundary sample replication is carried out using Fuzziness Guided Instance Replication (FGIR) to enhance the training distribution before re-training the classifier. By learning such a relationship instead of assuming manually defined thresholds, it provides a better means of achieving learning of robust decision boundaries [8, 11, 15]. The performance of proposed framework Evaluated using 10-fold stratified cross-validation on 10 benchmark datasets obtained from the UCI machine learning repository. These datasets are of diverse application domains, sizes, dimensions, and complexity levels. It was observed that the proposed AFW consistently improves the performance of baseline NNRw classifier in handling noisy boundary instances for a better classification performance while at the same time keeping the learning process stable even on datasets where the baseline performance is high. The study contributes to the knowledge by proposing an Adaptive Fuzziness Weighting framework which learns the instance importance dynamically from instance uncertainty instead of using predefined fuzziness thresholds, deriving an adaptive weighting function using meta-learning through Ridge Regression for modeling instance fuzziness and replication weights, and Fuzziness Guided Instance Replication (FGIR) for enriching the training data with important boundary instances. In summary, the proposed framework combines the benefits of uncertainty-aware learning, adaptive weighting, and instance replication to learn accurate decision boundaries from the training data.

2. RELATED WORK

Improving the performance of classifiers through better utilization of training data is a well-established area of research in machine learning. Many studies have focused on learning classification models by incorporating techniques such as instance selection, sample weighting, data resampling, uncertainty estimation, and meta-learning to increase robustness and generalization capabilities. These techniques largely seek to better capture the decision boundary by focusing on informative training instances while down-weighting less informative observations, thereby reducing reliance on erroneous and redundant data. Although substantial progress has been achieved in these directions, better exploiting training samples associated with ambiguous decision boundaries is still a research gap.

The concept of fuzzy set theory introduced in [3] provides a mathematical formalization to quantify uncertainty by enabling an instance to have fractional memberships in various classes. In supervised learning, fuzziness measures the ambiguity between the probabilities of different classes and is an interpretable measure of data uncertainty [1]. Unlike conventional binary classification, where a training instance must fully belong to one of the two classes, fuzzy representation of data can precisely characterize uncertainties regarding each sample via its memberships in each class, which makes them suitable for describing ambiguous boundary instances. In many classification problems, the posterior probabilities generated by machine learning algorithms for instances can be treated as an index representing their degree of fuzziness; instances with nearly equal posterior probabilities in many classes usually imply a higher degree of ambiguity, thus more difficult to classify [4]. It has also been shown that explicitly modeling uncertainty can contribute to improving prediction reliability, model calibration, and classifier robustness in many sensitive domains [5, 6].

Various studies have investigated methods of employing fuzziness and uncertainty for classifier enhancement. Efforts have been made by the authors in study [10] to develop a Divide-and-Conquer (D&C) approach where training instances are classified according to their fuzziness scores, concluding that ambiguous instances located at boundaries do not necessarily need to be discarded because they can contain essential information for class discriminability and boundary identification. In their approach, instances were clustered based on predetermined fuzziness values, allowing classification improvement by retaining valuable instances without the need to prune uncertain ones. However, their scheme depends on ad hoc defined and fixed thresholds across datasets with varied classification challenges. As a

consequence, the relationship between the uncertainty of a training instance and the optimal way to represent its information remains unaddressed. Likewise, study [9] proposed an Adaptive Reweighting Network (ARNet) which adds uncertainty calibration to deep learning models to adapt the influence of samples during training. These developments all indicate that there is a higher awareness that fuzziness, if used adaptively, can help to lead to better learning of data representation. The AFW framework builds on this, adding meta-learning-based fuzziness adaptation. Meta-learning is one of the most prevalent paradigms recently that allows models to “learn how to learn.” Meta-learning has been used in the area of instance weighting to optimize training dynamics, to increase robustness, and to handle data imbalance. The study [16] proposed Learning to Reweight (L2R) to adaptively change sample weights according to a meta-objective and extended this idea. These frameworks showed that learning the weights through a meta-learning process is more effective than heuristic rules, as it is more data distribution agnostic. Recently, uncertainty estimation has been included in meta-learning in extensions. Task Uncertainty Regularization in meta-learning was proposed by article [7, 17] which demonstrated that uncertainty learning over tasks leads to better cross domain generalization. Bayesian Meta-Learning for Deep Uncertainty Estimation [18] proposes to consider uncertainty a cue to model adaptation. Moreover, the studies have further enhanced the incorporation of fuzziness and meta-learning. In incremental learning tasks, [11] proposed to embed fuzziness indicators into the meta-objective to enhance the performance of the model.

In addition to fuzziness-based approaches, instance selection and data resampling are widely used to boost classification performance. Traditional instance selection techniques remove noisy or irrelevant training samples to simplify the learning problem and reduce computational burden, whereas data resampling methods address class imbalance. Oversampling increases the representation of minority class instances, such as in standard random oversampling and advanced techniques like Synthetic Minority Over-sampling Technique (SMOTE) [19] and Adaptive Synthetic Sampling (ADASYN) [20] which synthesize new minority instances. Despite the effectiveness of these methods in handling imbalanced data, they mostly overlook the individual instance uncertainty and can lead to learning noisy duplicates or poorly-constructed artificial data. Another active area of research for enhancing classifier learning is adaptive sample weighting, where training instances are assigned varied importance weights rather than treated equally [2, 8]. Recently, the field of meta-learning has been used to build effective learning-to-reweight strategies that automatically learn optimal sample weights from data. These frameworks [2, 8] learn weighting functions through optimization, making them more robust against label noise, distribution shift and other challenging scenarios. In parallel, uncertainty-aware learning methods aim to utilize uncertainty measurements for improving prediction calibration, reliability, and generalization [6, 9]. Nevertheless, current sample weighting schemes mainly leverage prediction errors or training losses and seldom incorporate direct measurements of fuzziness as proxies for instance uncertainty. In summary, fuzziness estimation, uncertainty-aware learning, adaptive sample weighting, and meta-learning have each demonstrated their own merits in improving classification. However, they have mostly been researched separately and few studies have attempted to integrate these ideas into a unified learning paradigm. Most current fuzziness-based learning techniques rely on pre-set thresholds.

Oversampling methods are designed to handle class imbalance but typically neglect instance uncertainty. Existing adaptive weighting algorithms mostly estimate sample importance based on classification errors but not directly on instance fuzziness. Hence, the potentially useful structural information within fuzzy training samples has not yet been fully explored. To fulfill the gap, the study proposes an Adaptive Fuzziness Weighting (AFW) framework that unites fuzziness estimation, adaptive meta-learning, and instance replication into an uncertainty-aware learning paradigm. Instead of adopting explicit fuzziness thresholds, AFW utilizes a [21] to automatically learn the relationship between instance fuzziness and replication weight. As a result, an efficient Fuzziness-Guided Instance Replication (FGIR) mechanism is devised to selectively oversample the most informative boundary instances, leading to better decision boundary learning and enhanced classifier generalization on a wide range of dataset difficulties.

3. METHODOLOGY

A novel supervised meta-learning instance selection and re-weighting method has been proposed for increasing the generalization performance of classifiers, especially those vulnerable to data distribution ambiguity. Unlike static threshold Divide and Conquer (D&C) schemes, AFW adapts the relationship between the calculated fuzziness of an instance and the probability of its correct classification in an online fashion, and then uses this relationship to assign a replication weight that maximizes the accuracy of classification. The methodology is broken down into three phases. Overall methodology for supervised meta-learning instance selection using adaptive fuzziness weighting is shown in figure 1 and algorithm

shown in Figure 2.

3.1 Dataset

To test the Adaptive Fuzziness Weighting strategy, 10 different benchmark datasets were used, mainly from the UCI Machine Learning Repository. The set was selected with the aim to include strong validation covering different classification complexities, scales and feature spaces. The datasets are very different in size from the smaller Wine dataset (178 instances) to the large-scale Pen-Based Handwritten Digits dataset (10,992 instances). This variation validates the method's robustness for various amount of data. The complexity of the classification tasks is also quite variable: from three classes (Wine) to eleven classes (Vowel). In this field of research, all features were pre-processed using Min-Max Scaling in order to normalize them prior to classification. Table 1 shows the characteristics of datasets used in experiment.

3.2 Phase 1: Base Fuzziness Quantification

The initial phase is used to set up the original model performance and measure the inherent ambiguity (fuzziness) of each of the instances in the evaluation set.

$$D_{test} = \{(X_i, y_i)\}_{i=1}^N$$

3.2.1 Initial Classifier Training (C_{base})

Initially a classifier, called C_{base} , is trained on the initial training set D_{train} . The base learner is the Neural Network with Random Weights (NNRW), which has been proved to be efficient and has a good performance for fuzziness-based methods.

Table 1. Detailed Characteristics of Datasets used in Experiments

Dataset Name	Domain	Instances	Features	Classes	Data Type
Wine	Chemical Analysis	178	13	3	Multi-class
Glass	Chemical Analysis	214	9	6	Multi-class
Cleveland (Heart)	Medical Diagnosis	303	13	5	Multi-class
Ecoli	Protein Localization	336	7	8	Multi-class
Automobile	Vehicle Specifications	392	8	6	Multi-class
Auto MPG	Vehicle Performance	392	8	6	Multi-class
Vehicle	Silhouette Recognition	846	18	4	Multi-class
Vowel	Speech Recognition	990	10	11	Multi-class
Yeast	Protein Localization	1,484	8	10	Multi-class
Penbased	Handwritten Digits	10,992	16	10	Multi-class

3.2.2 Fuzziness Quantification

The amount of ambiguity associated with each instance $X_i \in D_{test}$ is measured by the F measure based on the posterior probability matrix P yielded by C_{base} . The fuzziness for an instance X_i is determined by the maximum probability that is assigned to its true class,

$$\hat{p}_i = P(X_i|y_i)$$

Fuzziness Measure (F_i) is a maximum margin of certainty obtained by how close the instance is to a decision boundary:

$$F_i = 1 - \hat{p}_i = 1 - \max_{k \in \{1, \dots, C\}} P(k|X_i) \quad (1)$$

This will be done with the posterior probability of X_i being in class k , $P(k|X_i)$, and the number of classes, C . A high F_i value means that the instance X_i is highly ambiguous (close to a decision boundary), and the low F_i value means that high certainty.

3.3 Phase 2: Adaptive Weighting Learning Function (M)

In this phase, a meta-learning model, M , is trained to dynamically learn a re-weighting factor for the cost function, which depends on the fuzziness that is quantified in this step as opposed to a static threshold (as in D&C).

3.3.1 Defining the Target Variable

Mapping between the fuzziness F_i and classification correctness is modeled as the relation between fuzziness and classification confidence. z_i is binary and represents the outcome of interest:

$$z_i = \begin{cases} 1 & C_{base}(X_i) = y_i & (\text{Correctly Classified}) \\ 0 & C_{base}(X_i) \neq y_i & (\text{Incorrectly Classified}) \end{cases} \quad (2)$$

3.3.2 Adaptive Weighting Model (M)

A simple linear regression model M is created to predict the probability of correct classification (z_i) according to the fuzziness (F_i). We use Ridge Regression to mitigate the effects of multicollinearity and noise:

$$M : \hat{z}_i = f(F_i) = \alpha F_i + \beta \quad (3)$$

The parameters α and β are optimized by minimizing the penalized squared error for test set D_{test} :

$$\min_{\alpha, \beta} \sum_{i=1}^N (z_i - (\alpha F_i + \beta))^2 + \lambda(\alpha^2 + \beta^2) \quad (4)$$

where λ is the Ridge penalty hyperparameter.

4 Adaptive Weight Assignment (ω_i)

The adaptive weight ω_i is equal to the predicted probability z_i . This weight is then trimmed and scaled to have a fixed and bounded replication factor R :

$$\omega_i = \text{clip}(\hat{z}_i, \omega_{min}, \omega_{max}) \quad (5)$$

The weight $\omega_i \in [\omega_{min}, \omega_{max}]$ is inversely related to the final number of replications; it is weighted higher for instances predicted to be correctly classified (high z_i) which should have a higher chance of being replicated.

3.4 Phase 3: Fuzziness-Regulated Replication and Final Training (C_{final})

The last step is to add the acquired adaptive weights to the original training set D_{train} , and retrain the final refined classifier C_{final} .

3.4.1 Dataset Augmentation

The examples $X_i \in D_{test}$ are re-added back to the training set, but with weights ω_i . For each instance, the adaptive weight is scaled and rounded to give the replication factor R_i , which is limited to the maximum level R_{max} (e.g., $R_{max} = 5$):

$$R_i = \text{round}(\omega_i \cdot R_{max}) \quad (6)$$

The resulting training set D_{aug} is made by combining the original training set D_{train} with the copies of the test set D_{test} :

$$D_{new} = D_{train} \cup \{X_i, y_i \text{ replicated } R_i \text{ times} \mid (X_i, y_i) \in D_{test}\} \quad (7)$$

3.4.2 Final Classifier Training

The classifier C_{final} is trained with the extended dataset D_{new} . This will help to increase the influence of ambiguous but correct instances (high ω_i) during the training of the final model, thus “pulling” the decision boundary towards the high-density areas of correct but ambiguous data.

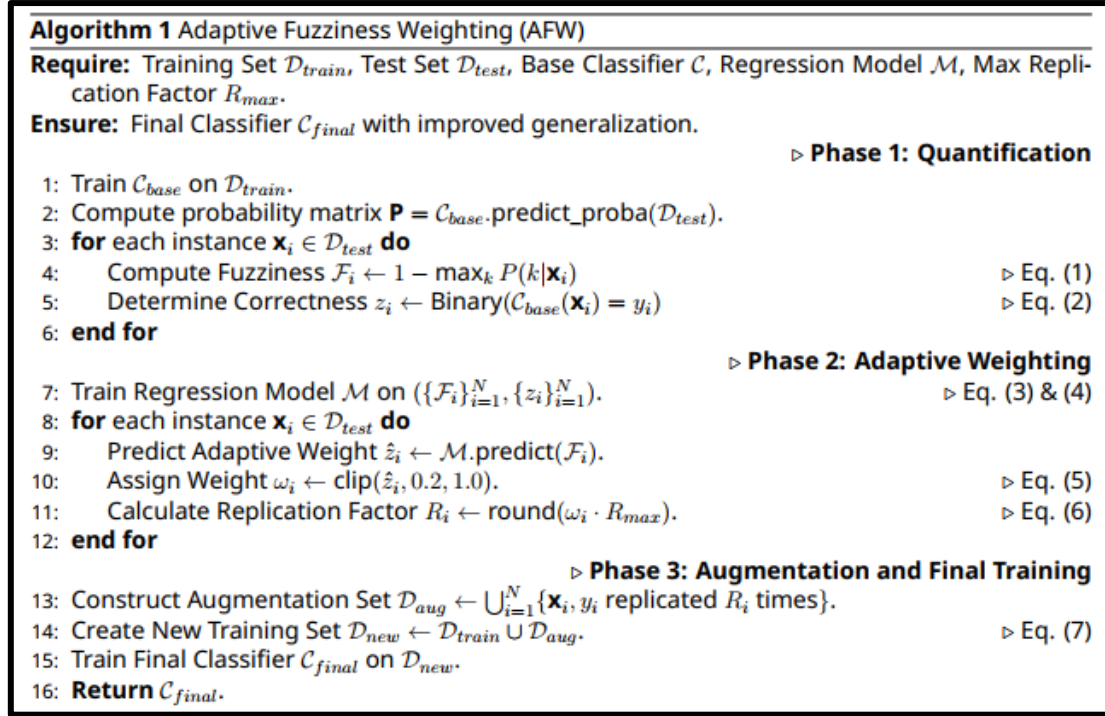


Figure 1. Algorithm of AFW

Table 2. Summary of Accuracy using Different datasets

Dataset	Baseline Accuracy (Accbase)	AFW Accuracy	Absolute Improvement	Relative Gain
Auto MPG	0.5969	0.8849	0.2880	48.3%
Automobile	0.3896	0.9175	0.5279	135.5%
Cleveland (Heart)	0.8044	0.8924	0.0880	10.9%
Ecoli	0.8538	0.9463	0.0925	10.8%
Glass	0.6351	0.9390	0.3039	47.8%
Penbased	0.9450	0.9534	0.0084	0.9%
Vehicle	0.9775	0.9929	0.0154	1.6%
Vowel	0.7606	0.9111	0.1505	19.8%
Wine	0.6017	0.9929	0.3912	65.0%
Yeast	0.5694	0.8354	0.2660	46.7%
Average	0.7134	0.9266	0.2132	29.88%

The results of the experiments show that the overall performance of the final classifier ($\mathcal{C}_{final}$) can be greatly improved in a wide variety of classification problems as shown in table 1 using AFW strategy. The main result is that the improvement is considerable, with an improvement rate of 21.32 percentage points (close to 30%) on average over the ten datasets. The mean accuracy rose from 0.7134 (Baseline) to 0.9266 (AFW). This confirms the key idea of the AFW methodology – learning about instances that are both ambiguous (high Fuzziness $\mathcal{F}$) and correctly classified (low Fuzziness ω) is an effective way to augment a dataset to refine the classification boundary as illustrated in a Figure 3.

The largest gains were seen in those datasets with the lowest Baseline Accuracy (including Automobile (+52.79%), Wine (+39.12%), Glass, Auto MPG and Yeast). In these datasets, the first classifier ($\mathcal{C}_{base}$) failed to learn a clear decision boundary thus resulting in a large number of instances being classified correctly, but close to the decision boundary (high $\mathcal{F}_i$ and $z_i = 1$). A strong correlation between the necessity of boundary reinforcement and high fuzziness was obtained by learning Adaptive Weighting Function ($\mathcal{M}$). In Phase 3, the high level of replication factor (R_i) was given to these critical and ambiguous-but-correct cases, which caused the final classifier's decision boundary to be "pulled" to the dense, confusing regions in the feature

space, resulting in highly effective generalization and better performance (e.g., 0.9929 for Wine accuracy).

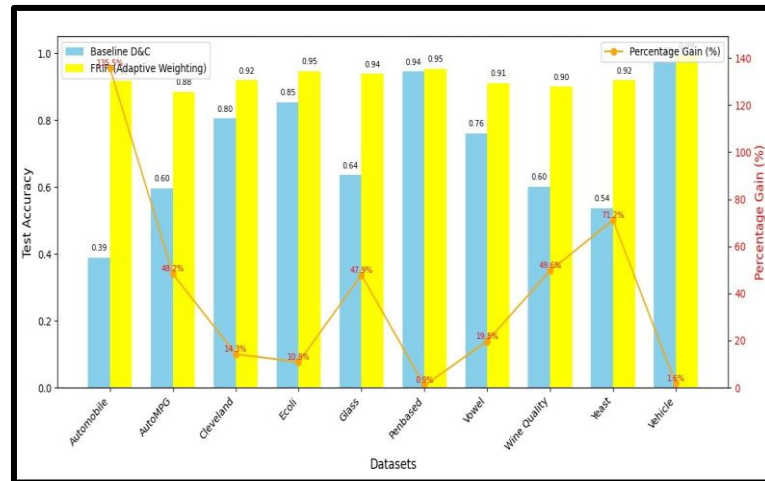


Figure 3. Comparison of Baseline vs FWS across UCI Datasets

Vehicle (+0.0154) and Penbased (+0.0084) were relatively unchanged, however, both datasets had a high Baseline Accuracy to begin with (0.9775 and 0.9450 respectively). This indicates that the first (C_{base}) classifier is strong for these problems, which suggests that most of the instances are either difficult ones (low F_i) or are always wrong or always right for each fold on the cross validation. In these scenarios, the adaptive weights ω_i would be low (for unambiguous points) or the initial classifier would have been already well optimized so that augmentation process does not significantly move the C_{final} boundary. This approach does not cause any degradation in performance and does not introduce any noise, suggesting that it is a stable method even if there is little room for improvement.

The Ridge Regression model as the Meta-learner M in Phase 2 was a successful strategy. The Ridge Regression model learned the relationship between fuzziness and correctness for each individual dataset and adaptively determined the optimal weighting ω_i . Unlike static methods that make a fixed choice in the selection of instances, the Ridge Regression model learned the relationship between fuzziness and correctness for each individual dataset and adaptively determined the optimal weighting ω_i . This is the payout mechanism for the AFW strategy, which is why it's able to achieve maximum gains in low-performing datasets and keep gains steady in high-performing datasets. This adaptive weighting is then used in the replication and augmentation step (Phase 3) to obtain a concrete benefit in terms of the training distribution for the final classifier.

5. CONCLUSION

The Adaptive Fuzziness Weighting strategy proved to be very successful and stable for improving the base classifier (NNRw) for a variety of classification problems. The main result is threefold: i) Significant Performance Gain: The average classification accuracy over the ten benchmark datasets showed a gain of 21.32% (close to 30% relative gain) for AFW methodology. This performance improvement confirms the basic idea of the AFW framework: ii) Adaptive Boundary Refinement – the key to this success is the strategic and three-phase augmentation of the training data by means of the use of fuzziness (ambiguity) and initial correctness. (iii) Maximum Impact on Complex Data: In datasets that were the most difficult for the initial classifier (such as Automobile and Wine), the biggest advantage of the method was observed, indicating its high capability of stabilizing and improving classification in complex data environments with ambiguous classification. Moreover, the impact of this data distribution on already good datasets like Vehicle and Penbased is minimal, which confirms its stability, since noise would not be introduced when the distribution of the data is already well established. Overall, AFW is able to convert instance uncertainty (fuzziness) into a quantifiable training emphasis (adaptive weight), and offers a practical and general solution to constructing better and more robust classification models.

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