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Ensemble Learning Improvement through Reinforcement Learning Idea

Mohammad Savargiv [a], Behrooz Masoumi [a,*], MohammadReza Keyvanpour [b]

[a] *Faculty of Computer and Information Technology Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran*

[b] *Department of Computer Engineerin, Alzahra University, Tehran, Iran*

Abstract

Ensemble learning is one of the learning methods to create a strong classifier through the integration of basic classifiers that includes the benefits of all of them. Meanwhile, weighting classifiers in the ensemble learning approach is a major challenge. This challenge arises from the fact that in ensemble learning all constructor classifiers are considered to be at the same level of distinguishing ability. While in different problem situations and especially in dynamic environments, the performance of base learners is affected by the problem space and data behavior. The solutions that have been presented in the subject literature assumed that problem space condition is permanent and static. While for each entry in real, the situation has changed and a completely dynamic environment is created. In this paper, a method based on the reinforcement learning idea is proposed to modify the weight of the base learners in the ensemble according to problem space dynamically. The proposed method is based on receiving feedback from the environment and therefore can adapt to the problem space. In the proposed method, learning automata is used to receive feedback from the environment and perform appropriate actions. Sentiment analysis has been selected as a case study to evaluate the proposed method. The diversity of data behavior in sentiment analysis is very high and it creates an environment with dynamic data behavior. The results of the evaluation on six different datasets and the ranking of different values of learning automata parameters reveal a significant difference between the efficiency of the proposed method and the ensemble learning literature.

Keywords: Ensemble Learning, Reinforcement Learning, Learning Automata, Improvement, Sentiment Analysis.

1.Introduction

One of the techniques to increase the efficiency of classifiers is to integrate them into an approach called ensemble learning. The goal of ensemble learning is to achieve the benefits of all classifiers. However, different classifiers exhibit different functions in different problem situations. To improve the efficiency of ensemble learning, the performance of each classifier in different conditions should be evaluated, and based on that, the impact of that classifier in the final result should be determined. If the classifier performs well in a particular situation, it should have the same amount of impact on the final result, and vice versa. Since this approach is based on receiving feedback, it can be guaranteed that ensemble learning efficiency will have the highest achievable value.

To evaluate the proposed method, the field of sentiment analysis has been selected. Data behavior in sentiment analysis is a dynamic behavior. This means that in different situations, different and even contradictory behaviors of data (i.e. text tokens) can be seen.

Understanding the position, attitudes, and opinions of individuals about a single entity has many applications. Due to the fast growth of social networks and their proliferation and also by attention to the existence of the type of text data that has the largest volume of content in these applications, the significance of sentiment analysis (SA) in the text reveals further. S.A. has a wide range of applications, including movie box-office performance prediction [1], stock market performance prediction [2], predicting

elections [3], [4], analysis of a specific topic sensation in multimodal social networks such as YouTube, Instagram, and Twitter [5], [6], news and blogs [7], [8], proposing systems [9], and business intelligence [10], customer feedback analysis [11], [12], and so on.

The behavior of textual data is dynamic because it can be noisy and highly unstructured, and the use of basic polarity of the words used in the text to analyze the sentiment does not meet all the requirements of the problem. The term "noise" refers to informal writing, and the extensive use of acronyms and abbreviations. And also the dynamism of the problem space refers to the existence of words with default polarity that may have different polarities in different domains. For example, in the electronic domain, the word 'small' has a positive polarity, while in the restaurant domain, the same term has a negative polarity. On the other hand, the adjectives in the text have a great ability to change the level of word polarity. The change in the polarity value of a word may change the polarity of the entire document. Also, unrealistic words such as: maybe, and wish change the polarity of the sentence.

Another case in the data challenge group is the existence of words that are written with the repetition of one of the letters. These words are usually polarized, but their writing style has a significant impact on the level of the polarity. For example words like 'gooooood', 'badddd'. The existence of non-linguistic words such as emoticons that contain polarity is another challenge in this area.

The proposed method assigns proportionate impact weight to the base learners of the ensemble according to the behavior of data. Assigning the impact weight is done by use of learning automata. The learning automata can adapt itself to the problem space, and it can decide its next step according to the current situation and the history of performance.

The main contributions of this paper are summarized as follows.

We propose a method based on reinforcement learning idea to improve the performance of

ensemble learning by learning automata for sentiment analysis.

The proposed method is a domain-independent method since it operates based on the received feedback from the environment.

The proposed method is an adaptive method for dealing with dynamic problem space.

The experimental result proves the efficiency of the proposed method versus traditional methods.

The rest of the paper is organized as follows. In section 2 the related works are presented. Learning automat is introduced in section 3. The proposed method is explained in section 4. Section 5 and section 6 present evaluation and discussion respectively. Conclusion and future work are placed in section 7.

2.Related Works

The purpose of the ensemble methods is to improve the efficiency and increase the accuracy of the identification process. It is done by using the aggregation of base learners. In the ensemble learning approach, the training and testing phases are done for each base learner individually and the result of them are evaluated in an aggregated mode in the next step.

Three ensemble learning methods are Bagging, Boosting, and Random Subspace. In the Bagging, constructor classifiers are made by using random independent bootstrap replicates from the set of training data. The final result is calculated by majority voting. This method of the ensemble is often used when the size of the data is limited [13]. In Boosting, constructor classifiers are made based on weighted versions of the training set. Weighting to the training set is based on the history of classifiers performance. The final result is also done using simple voting or weighted voting. In Random Subspace, constructor classifiers are made by using the random subfields of the feature set [14].
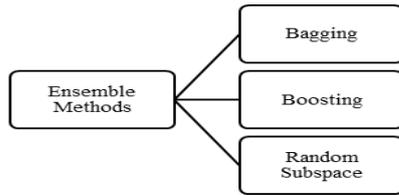
Fig. 1. Ensemble learning method categories

The ensemble learning is implementable in two styles: homogeneous base learners and heterogeneous base learners. In the first style, all of the base learners are the same and they are located in the same level of separate ability. The random forest is the well-known homogeneous ensemble learning method in which all its base learners are the decision tree. In another style, the base learners can be from different classifiers with different abilities. It's clear in heterogeneous base learner style, the need to assigning weight to them according to their performance is essential and undeniable.

The main advantage of the ensemble learning approach is the use of all base learner's strength points. There is no constraining at the ensemble learning on the type and the number of base learner selections. This approach provides the possibility to organize base learners in the arbitrary mode.

The main challenge of ensemble techniques is how to assign a weight to the base learner of the ensemble to achieve better performance and higher precision. The majority voting is the simplest way [15], in which static weights are assigned to each base learner and it remains unchanged during the process [16]. It is clear although it may perform better performance than the basic methods, however, it will not perform well in general, because both strength and weakness points have given more weight due to the constant assigned coefficients [17].

To solve the problem of weighting the base learners, a dynamic method is proposed in [18]. Since different classifiers have different resolution capabilities, different weights have been taken into account for each of the base learners to achieve the most partial resolution in the ensemble. In this method, true positive, true negative, false positive, and false negative factors were used for dynamic weight. In [19], a cost-sensitive combination technique is proposed that combines classifiers using sequential three-way decisions and grouping objects. The aggregation is done by minimizing the total cost consisting of misclassification cost and time cost. The proposed idea in [20] is based on decomposing and clustering time series to create a center of clusters to improve prediction effectiveness. The auteurs of [21] have proposed a method based on the combination of SVR, ANN, and DT classifiers for solar irradiance prediction. A method based on homogeneous ensemble learning is suggested by [22] that all base learners are kNN. Gaussian Naive Bayes, Multinomial Naive Bayes, Bernoulli Naive Bayes, and Decision Tree classifiers are used by [23] to create ensembles for spam detection. In [24], different ensemble strategies for facial expression recognition are compared. The authors of [25] have used the ensemble for drug-target interactions. The ensemble approach is used for XSS attack detection by [26]. HMM, integration for cross-view gait recognition is used by [27]. An ensemble-based method for skeleton-based 3D action recognition is proposed by [28]. Double-level ensemble learning is presented by [29] for anomaly detection. Distributed ensemble learning is used by [30] to achieve a little overhead. Software fault prediction by ensemble techniques investigated by [31]. The random forest is used as one of the base learners of the ensemble model for fake news detection by [32].

In [33], a framework is provided to weighting the ensemble based on the reference dataset for an inferior high-resolution (HR) image. A method for the recognition and classification of diseases by ensemble learning is presented by [34]. In [35], the hierarchical ensemble of an extreme learning machine is proposed. In [36], an ensemble-based method with three LR, NB, and Multilayer perception classifiers is proposed for disease diagnosis. In [37], a method based on the ensemble of probabilistic neural networks and majority voting is proposed for outlier detection. Weighted ensemble learning aimed at maximizing diversity and individual accuracy simultaneously is presented by [38]. In [39], a weighted ensemble with decision tree classifiers, gradient boosted trees and the random forest is proposed for big data time series forecasting. The weighting method is based on the weighted least square method and it is static. The authors of [40] propose an ensemble-based method consisting of

SMV and KNN, which is proposed to improve the robustness in traffic incident detection.

The most prominent research activities related to the ensemble-based approach in the field of opinion mining have been collected in [41]. In addition to methods such as Fuzzy logic, ensembles made with SVM and LR have also been used in [42] for text processing. This article provides a mechanism for rating Twitter users using an SVM ensemble. NB is another classic classifier used in [43] as an ensemble. In [44], by combining EM, NB, and SVM classifiers, an ensemble is proposed that performs better than the three classifiers. Random Forest, which is an ensemble, has been used in [45] for emotion analysis. A combination of heterogeneous data types has been proposed in [46] for the analysis of messages in social networks. In [47] RF has been used for evaluation. The method used RF is classic and, there is no mention of weighting the ensemble classifiers. In [48] RF is also used as one of the classifiers in the classification phase. In [49] RF has been used for classification because of its high efficiency and accuracy. The authors of [50] used an ensemble to initialize the neural network inputs for sentiment indicator. This ensemble contains NN, SVM, and RF classifiers and performs the results by averaging the ensemble classifiers output. The purpose of [51] is to investigate the effect of pre-processing on emotion analysis in which in addition to classical classifiers, RF is also used as one of the classifiers for evaluation. A pseudo-ensemble method based on Gaussian parameter fuzzing and latent subspace sampling is proposed by [52]. This article does not discuss the weighting of child-derived classifiers. The ensemble learning approach is used by [53] to combine different classifiers used in multi-view to identify comments for opinion spam detection. The proposed method in this article has used various aspects such as linguistic, psychological, quantitative textual features. Obtained features from different views are ranked, and k-NN, NB, and SVM are used to form the ensemble.

Ensemble learning based on meta-level features is a proposed approach by [54]. The meta-level features are the outputs of each of the vocabulary methods and sources used for emotion analysis. This approach uses the majority voting to create the ensemble, and it generates the ensemble using the five constructor classifiers such as NB, ME, DT, KNN, and SVM by triple mode i.e. bagging, boosting, and random subspace. The authors of [55] used Random Forest, SVM, Naive Bayes, and Logistic Regression classifiers to create the ensemble. In [56] a domain-independent approach with an unsupervised ensemble learning approach for clustering is proposed to perform k-means algorithm analysis. In [57] a method based on Hidden Markov Models is proposed to classify the text. The proposed method is ensemble-based and uses a predefined sentiment lexicon instead of a set of predefined emotional vocabulary tokens. The proposed method is also capable of extracting the implicit sentiment contained in the text. A multi-view ensemble learning approach has been suggested in [58] to identify bugs in production forums from online forums. In the proposed method, different combinations of the features related to different domains are used to create multi-visibility ensembles. A hybrid ensemble pruning scheme based on clustering is proposed by [59] to classify emotion in context. In the proposed method, at first, base learners are clustered based on attributes, then two classifiers from each group are selected as candidate classifiers based on pairwise diversity. The proposed method in [60] is based on different combinations of data, and it used classifiers such as ANN, DT, and RF to create different prediction models.

Many research activities have used ensemble learning for the classification process. However, we tried to investigate the newest and more related references of the subject literature during recent years. As can be seen in the brief review, among all the previous works, only [33], [39], [40], and [18] include ensemble weighting. Nevertheless, all weighting methods used in the mentioned references are static, and assigned weight to base learners are permanent in the face of new problem space. On the other hand, research activities that have used ensemble learning to aggregate base learners fall into four categories. Table 1 presents the characteristics of all four types of aggregation.

Table 1

Characteristics of different types of aggregation in ensemble learning

Aggregation type	Description	Advantage	Challenge
Simple Voting	Create an ensemble using different splits of similar training data and base learners, or similar training data and different base learners	simplicity	Consider the resolution of base learners at the same level Unsuitable for environments with high variations
Averaging	Calculate average predictions per sample	Reduce the possibility of overfitting and create a smoother regression model	Unsuitable for dynamic environments
Majority Voting	Assign a test sample to a class if more than half of the votes are received from base learners	Higher efficiency compared to simple voting and averaging	Nonstable prediction occurs if more than half of the votes are not received The value of the votes received from the base learners is assumed to be the same
Static Weighted Voting	Assigning weights to base learners to achieve higher efficiency in the classification	Increased efficiency compared to Majority Voting	Inability to manage variable data behavior

3.Learning Automata

Learning Automata (LA) is one of the learning algorithms that, after selecting different actions at different times, it identifies the best practices in terms of responses received from the environment. LA selects an action from the set of actions in the vector of probabilities, and this action is evaluated in the environment. By using the received signal from the environment, the LA updates the probability vector and, by repeating this process, the optimal action is identified gradually. Finding the global optimum in the solution space is another advantage of using the LA.

The LA can be represented formally by the quadruple $LA= \{\alpha, \beta, P, T\}$ in which $\alpha= \{\alpha_1, \alpha_2,..., \alpha_r\}$ is the set of actions (outputs) of the LA, or, the set of inputs of the environment. $\beta= \{\beta_1, \beta_2,..., \beta_r\}$ is the set of inputs of the LA or the set of outputs of the environment. $P= \{P_1, P_2,... , P_r\}$ is the probability vector of the LA actions and $P(n+1) =T[P(n), \alpha(n), \beta(n)]$ is the learning algorithm.

In the LA, three different models can be defined for the environment. In the P-Model, the environment presents the values of zero and one as output. In the Q-Model, the output values of the environment are discrete numbers between zero and one. In the S-Model, the output of the environment is the continuous value between zero and one. The selected actions by the LA are updated by both the signal received from the environment and using reward and penalty functions. The amount of allocated reward and penalty to the LA action can be defined in three ways: LRP, where the number of rewards and penalties are considered the same, LRεP in which the amount of penalty is several times smaller than the reward and LRI in which the penalty amount is considered zero [61].

To improve ensemble learning performance using reinforcement learning ideas, the use of LA is suggested in this paper. Interesting features of LA are the reason for choosing this tool [62], [63]. These features are summarized below.

- The LA presents an acceptable performance in an uncertain situation.
- The LA does search action in probability space.
- The LA requires simple feedback from the environment for optimizing its state.
- Since the LA has a simple structure, it has a simple implementation on both software and hardware.
- The LA isn't constrained to use accuracy criteria for optimization usage.
- The LA is applicable in real-time usage since the LA isn't involved with high computational complexity.
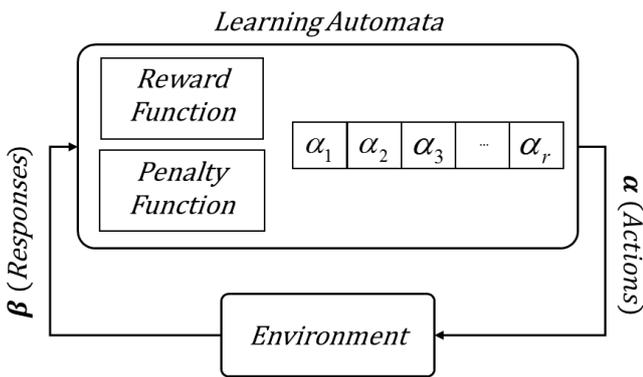
Fig. 2. Learning Automata Schema

4.Proposed Method

In this section, the structure of the proposed method is described in detail. Its structure is composed of a few simple components. Each component is placed in different blocks in the block diagram.

Conventional methods for aggregating classifiers to create a stronger classifier do not take into account the resolving power of classifiers under different conditions. Among the traditional methods, only Static Weighted Voting distinguishes between different base learners. Of course, it should be noted that this method is a static weighting method. There are some challenging points about this method. First, how to determine the initial weight of base learners involves its challenges. Second, during the classification process, the impact weights assigned to the base learners will remain constant. And the third point is that if there is an error in the output of the base learner, that error also receives a high impact weight and the final result of the ensemble is reduced.

The connection that can be imagined between the proposed method and the traditional methods of aggregating base learners is that in the proposed method, an attempt has been made to improve the three challenging points mentioned for Static Weighted Voting by using reinforcement learning idea.

As we knew, deterministic responses are not receivable from the base learners in the processes that run in the ensemble model. i.e., for each test entry, various responses may be received from the base learners. The environment has dynamic behavior. The best practice for weighing the base learners is the dynamic weighting per individual input. Due to the dynamic nature of the problem space and also to create adaptability, in this paper, the learning automata has been applied. The goal of the proposed method is to achieve higher accuracy in processes performed by the ensemble. According to the subject literature, achievement to the above benefits will only be possible if in addition to the fact that weighting should be done dynamically, at the same time the weighting should be adapted according to the problem conditions. Therefore, in the proposed method, the linear learning automata is used to select the base learners in the ensemble. The block diagram of the proposed method is shown in Figure 3.

The proposed method is based on the ensemble idea. Since heterogeneous classifiers present different performances in different situations, we create an ensemble in the heterogeneous model for the proposed method. To implement the proposed method, four different classical classifiers have been applied. They are SVM, Random Forest, Naïve Bayes, and Logistic Regression.
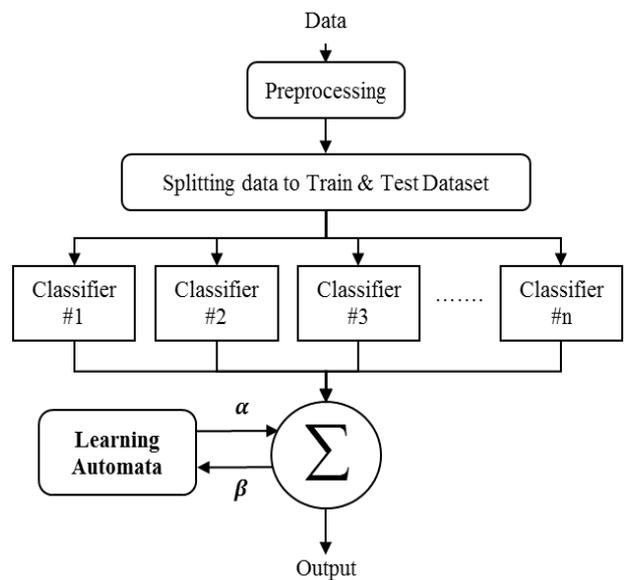

Fig. 3. Block diagram of the proposed method

4.1. Pre-Processing

Since the proposed method operates independently for the domain, so the pre-processing step is performed according to the data type. In general, the most basic pre-processes are noise reduction (removal), normalization, dimension reduction, BoW creation, etc.

4.2. Splitting Data To Train & Test Dataset

In this step, the used datasets are divided into two parts: train data and test data. In this paper, we use K-fold cross-validation for this step.

4.3. Ensemble

As noted above, the main purpose of the proposed method is the creation of reconfigurable adaptive ensemble learning based on the problem conditions and its inputs, to achieve the most efficiency at the output. Hence, the base learner integration process in the ensemble is performed by the LA, for this purpose, for each input in the test set, a linear LA is defined and the action of each LA corresponds to selecting the base learners.

In the Proposed method, the probability of the initial selection of base learners (i.e. the probability vector of actions in the LA) is not considered equal because the functionality of the base learners in the ensemble is not the same. Therefore, by using the function named "Weight Calculation", the probability of the initial choice of each classifier is calculated. The primary probability of selecting the base classifiers in the ensemble is the ratio of the performance of each base classifier over the total performance. Due to the above calculations, the probability of choosing powerful base classifiers is increased, and the probability of choosing weaker base classifiers is reduced. This is the first point of differentiation and strength of the proposed method versus all available methods in the subject literature. The "Weight Calculation" function is shown in Figure 4.

Function Weight Calculation
1:      **input**
2:        $D_i = \{ D_1 , D_2 , \ldots , D_n \}$: dataset containing data to be specified
3:      **output**
4:        $W\_C_i = \{ W\_C_1 , W\_C_2 , \ldots , W\_C_n \}$: weight of classifiers
5:      **assumption**
6:        $C_i = \{ C_1 , C_2 , \ldots , C_n \}$: a list of classifiers in ensemble
7:      **algorithm**
8:        **for each** C_i **in** ensemble **do**
9:            **Training** C_i
10:          **Testing** C_i
11:         **Calculate** $accuracy\_C_i$
12:        **end //for**
13:        $W\_C_i = accuracy\_C_i / \Sigma \ accuracy\_C_i$
14:      **end //algorithm**

Fig. 4. Calculation function for the initial selection of base learners in the proposed method

4.4. Learning Automata Block

In the Proposed method, the environment is assumed P-Model, which only has zero or one value at the output. In the ensemble test, for each input in the test set, a linear LA is defined. The probability of initially choosing the LA actions is equal to the values calculated by the Weight Calculation function, and the LA actions correspond to the choice of one of the base learners in the ensemble. For each time that a base classifier is selected, the LA receives a reinforcement signal from the environment and it updates the probability vector based on the received signal. At the received signal from the environment, if the selected base classifier has correctly identified the input test sample, the LA action (i.e. choosing a classifier) will be rewarded, otherwise, it will be penalized. The selection process will be continued until choices converged into one of the LA actions. After convergence, the ensemble finishes its final decision based on the selected base learner, and then it announces the result. The function of the ensemble named "Decision Maker" is shown in Figure 5.

Function Decision Maker
01: **input**
02:     $D_i = \{ D_1 , D_2 , \ldots , D_n \}$: dataset containing data to be specified
03 **output**
04:     Result
05: **assumption**
06:     *LA*: a learning automata
07:     α_i : (LA action) Choose C_i
08:     **a**: reward parameter
09:     **b**: penalty parameter
10:     **r**: the number of classifiers in the ensemble
11: **algorithm**

```
12:    for each D_i in test set do
13:      Selection_Probability = { W_C_i }
14:      Repeat
15:        the LA chooses one of its actions randomly, Let it be α_i
16:        if C_i predicts correctly
```

$$\begin{cases} p_i(n+1) = p_i(n) + a[1 - p_i(n)] \\ p_j(n+1) = (1-a)p_j(n), \ \forall j \ ; j \neq i \end{cases}$$

```
17:
18:        else
```

$$\begin{cases} p_j(n+1) = (1-b)p_i(n) \\ p_j(n+1) = \dfrac{b}{r-1} + (1-b)p_j(n), \ \forall j \ ; j \neq i \end{cases}$$

```
19:
20:        end // if
21:        Until LA convergences to an action or it exceeds
           predefined iteration number
22:      return C_i
23:      Result = the prediction of C_i
24:    end //for
25: end // algorithm
```

Fig. 5. The "Decision Maker" function in the proposed method

Due to the above calculations, it is possible to assign the coefficient of influence to the various base classifiers in the ensemble. The assignment of the coefficient of influence is based on the different conditions of the input samples as well as the different received reinforcement signals from the environment. The coefficient of influence is carried out adaptively. This is the second point of strength and differentiation of the proposed method versus all available methods in the subject literature.

5. Evaluation

In this section, the used data sets and the experimental result are described. All used data sets and their specifications are introduced in detail in the first subsection. The second subsection contains the experimental result.

5.1. Datasets

To evaluate the proposed method, the six following data sets are used. Textual data has the highest diversity among different types of data. The datasets used in this paper all contain textual data and include a different opinions in different domains. Placing a text token in different domains causes various behaviors. Tokens such as adjectives in different domains can change the polarity of a sentence to both positive and negative polarity. For example, in the healthcare domain, a word like "strong" would have a

positive polarity if the focus was on a drug, and a negative polarity if the focus was on the power of a viral disease. Therefore, textual data have been selected to evaluate the proposed method.

The selected text datasets are standard benchmarks in the field of opinion mining. The detail of these datasets is explained as follow.

Stanford – Sentiment 140 corpus
This dataset contains 1,600,000 tweets for sentiment analysis systems whose instances are labeled with both positive and negative labels [64].
Large Dataset of Movie Reviews
The data collection includes 50,000 comments on cinematic films [65]. These comments are organized in both positive and negative directions.
Sentence Polarity Dataset v1.0
This data set [66] consists of processed 5331 positive samples and 5331 negative samples.
Internet Movie Database
This data set [67] consists of 1400 samples, of which 700 samples are labeled with positive marks and another 700 samples are labeled with negative marks.
Yelp Review
This dataset [68] contains 560,000 training samples and 38,000 testing samples.
Amazon Review
This data set [68] consists of 800,000 training samples and 200,000 testing samples.
All of the above text data sets contain the real opinion of individuals in different domains. Both the high volume of data and the diversity of their domain were the best options for their selection for our evaluation.

5.2. Experimental Results

For evaluation, the proposed method is compared with four basic classifiers and two classic ensembles. The basic classifiers are Nave Bays (NB), Random Forest (RF), Support Vector Machine (SVM), and Logistic Regression (LR). The first classic ensemble performs the majority voting (MV) approach and the second performs the weighted voting (WV) approach. Through mentioned four basic classifiers, and according to the subject literature, the RF and LR yield better outcomes rather than the others. Since we increase their influence coefficient in the WV approach twice.

Since the Proposed method architecture is based on LA, all three forms of L_{RP}, $L_{R\varepsilon P}$, and L_{RI} are

intended. In this evaluation, we tune reward and penalty in different values.

The LA model environment is assumed to be the P-Model, where the environment defines zero and one values as outputs. Zero means to reward and one means penalty. If the correct answer is received from the selected base learner by the LA, the action of choice will be rewarded, otherwise, it will be penalized. To ensure the performance of the proposed method, each of three different models of the LA was repeated 1000 times in the K fold cross-validation for k=10.

The experimental result of the proposed method on six introduced data sets is presented as follows. Tuned values for reward and penalty parameters for each triple mode of the LA and the performances of these tuning are shown in Figure 6 to Figure 11 separated by datasets.

The focus of the evaluation is on the amount of improvement in the accuracy criterion compared to traditional methods in the literature. In this paper, we do not claim to improve factors such as execution time or complexity of the algorithm. Investigating the improvement in such factors is not the scope of this paper.
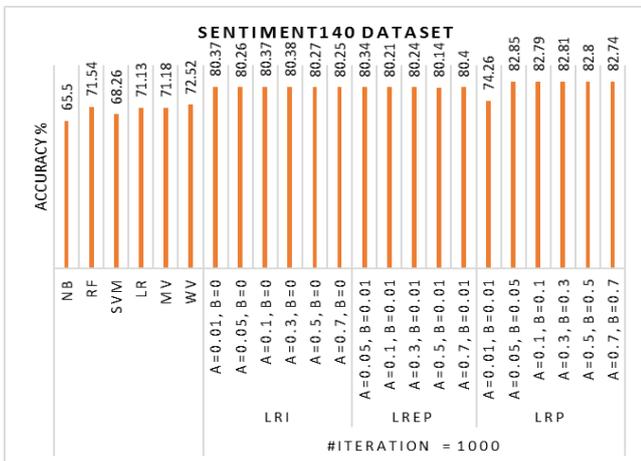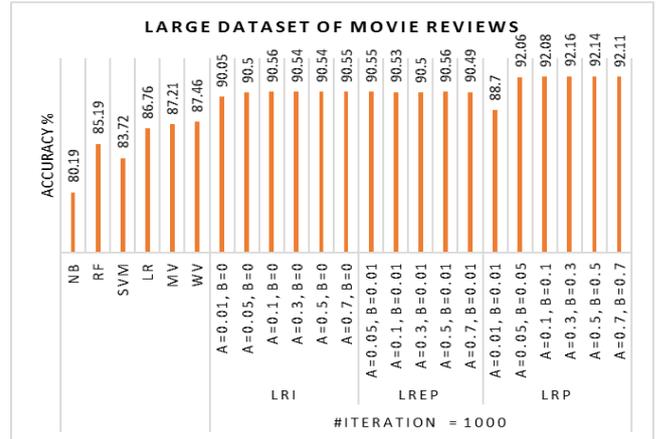

Fig. 7. The experimental result on Large Dataset of Movie Reviews
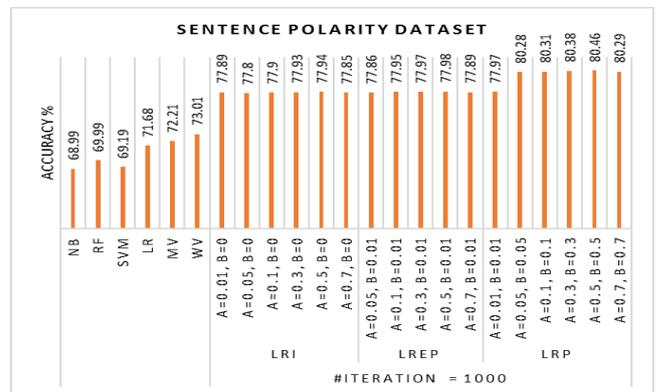
Fig. 8. The experimental result on Sentence Polarity Dataset v1.0

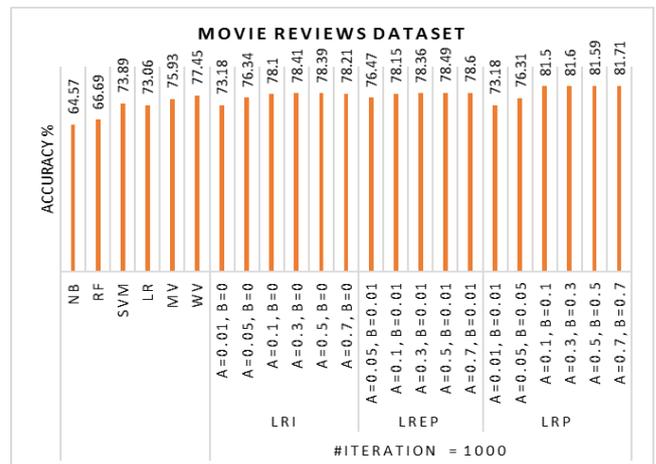Fig. 6. The experimental result on Stanford – Sentiment 140 corpus

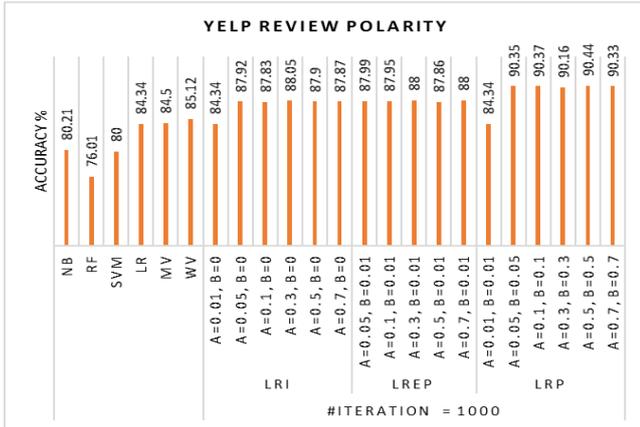Fig 9. xperimental result on Internet Movie Database

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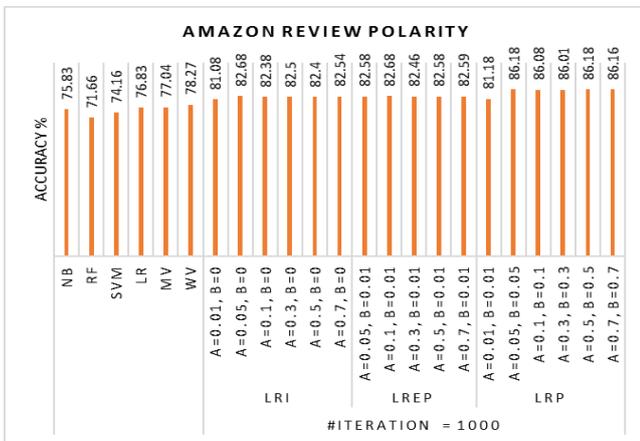Fig. 10. The experimental result on Yelp Review Dataset

Fig. 11. The experimental result on Amazon Review

It can be seen there is a significant difference between the mean accuracy of the proposed method, and both four base classifiers and two ensemble methods. This difference is a demonstrator of the strength of the proposed method. According to the experimental result, the proposed method provides more improvement on ensemble learning approaches versus traditional methods (e.g. weighted voting and majority voting). The evaluation of the proposed method is shown separated by executable modes of learning automata in each dataset. This presentation form of experimental result prepares comparison among different tuning values of reward and penalty parameters. Similar performance has appeared when the learning automata are adjusted in LRI and LRε P modes since the penalty parameter are considered zero or near to zero on them. Nonetheless, the experimental result of these two modes has a significant difference versus traditional approaches. On the other side, it is seen in the LRP mode which reward and penalty are equal, there is more improvement on the performance of ensemble learning. It should

be noted that in the LRP mode with a=0.01 and b=0.01 since the penalty parameter is tuned similar to two other modes (i.e. LRI and LRε P), there is no more improvement. Nonetheless, the performance of this tuning is better than the performance of the traditional approaches.

The difference between the weakest mode of the proposed method and the strongest mode of mode in the subject literature manifests the high strength of the proposed method for ensemble learning improvement.

6.Discussion

To ensure the effectiveness of the proposed method, Friedman Test has been done [69]. The results of the Friedman Test statistical verification are shown in Table 2. In this verification, the proposed method has been compared with four classical classifiers and two ensemble approaches. The results of the ranking show that the proposed method is improved versus the current approaches.

Friedman's test scores in Table 2 are valid proof that the proposed method is more improved than current approaches. As can be seen, all three signal modes considered for the proposed method yield far higher ratings than both classical classifiers and ensemble approaches. On the other hand, it is observed that the proposed method has better performance at the LRP mode where the rewards and penalties are equal.

The weakest performance on LRP mode occurs when a=0.01 and b=0.01. In this tuning, the penalty parameter tuned similar to LRI and LRε P where b is zero or it is near to zero. Although this tuning yields weak improvement it gains higher rank rather than base learners and traditional methods for ensemble learning.

According to the obtained ranking from the Friedman test, the base learners gain the lowest ranks and two ensemble approaches reach few better ranks. Through the two mentioned ensemble approaches, there is no significant improvement on the weighted ensemble. The best traditional improved method (i.e. weighted voting) is very few better than the weakest mode of the proposed method (i.e. LRI with a=0.01, b=0). Their deference is 0.17 on mean rank and

they gain successive final rank. In the overall view, the LRP mode presents higher improvement and it gains a mean rank upper than 18.

Table 2

The Friedman test ranking of the proposed method versus similar approaches

Method		Mean Rank	Final Rank
LRP	a=0.5, b=0.5	22.08	1
LRP	a=0.3, b=0.3	21.17	2
LRP	a=0.7, b=0.7	20.67	3
LRP	a=0.1, b=0.1	20.50	4
LRP	a=0.05, b=0.05	18.75	5
LRI	a=0.3, b=0	15.08	6
LReP	a=0.7, b=0.01	14.83	7
LReP	a=0.5, b=0.01	14.50	8
LReP	a=0.1, b=0.01	13.58	9
LReP	a=0.3, b=0.01	13.42	10
LRI	a=0.5, b=0	13.25	11
LReP	a=0.05, b=0.01	13.17	12
LRI	a=0.1, b=0	12.58	13
LRI	a=0.7, b=0	12.25	14
LRI	a=0.05, b=0	11.67	15
LRP	a=0.01, b=0.01	8.17	16
Ensembles	Weighted Voting	7.17	17
LRI	a=0.01, b=0	7.00	18
Ensembles	Majority Voting	5.50	19
Base Learners	Logistic Regression	3.83	20
Base Learners	Support Vector Machine	2.67	21
Base Learners	Random Forest	2.50	22
Base Learners	Nave Bays	1.67	23

To prove the independence from the domain, the proposed method has been executed on six separate text datasets. The results show that, in all domains, the functionality of the proposed method is better than other methods. This is a clear testimony to the correctness of the above claim.

Since the proposed method works independently from the domain, the need to assign the weight of polarity to the feature of text (i.e. tokens and vocabularies) is eliminated. Assigning the polarity weight to the feature of text performs acceptable performance when the process is done in the specific domain, otherwise, if we faced multi-domain in our process, this idea will not perform well.

When the number of classes increases and also when the number of samples increase, the efficiency of the algorithm will be dropped and the expected performance will be lost. This phenomenon is the main challenge of all the previous data mining methods. However, based on the experimental result and evaluations, and due to adaptability capacity, the proposed method is not involved with this type of restriction, and if both the number of classes and the number of samples increase, there is no loss of performance in the proposed method.

The performance of the proposed method faced with a diversity of data shows that the area of expertise of the proposed method is not limited to specific applications and given the adaptability capacity, it is possible to apply the proposed method to all applicable data mining issues.

7.Conclusion And Future Work

In this paper, an improved method for ensemble learning was proposed. The proposed method is based on learning automata, and its main purpose is to assign the coefficient of influence to the base learners used in the ensemble learning approach. The assignment of the impact coefficients to the base learners is based on the behavior of the data, and it is updated according to the problem condition in adaptable form. The proposed method works completely independently of the data domain and has no restrictions in the applied field. How to create an ensemble that has been proposed in the proposed method has eliminated the need to aggregate the output of base learners (e.g. majority voting or averaging). The evaluation results indicate a higher value in the accuracy criterion by the proposed method, which has a significant difference from the previous methods. The combination of ensemble learning with a multimodal approach through automata learning is the future direction of authors.

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