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AN IMPROVED RULE-BASED CLASSIFICATION WITH DYNAMIC THRESHOLDING BASED APPROACH FOR PREDICTION OF MEDICAL DATASET

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***Abstract*—** The rule-based classification algorithm now includes a dynamic threshold value. The significance of threshold values, classification algorithms that use threshold values, issues with setting static threshold values and dynamic threshold values, and rule generation. However, for some datasets, it is necessary to have a large number of rules, and for those datasets, a greater number of rules should be extracted, which affects reduction of generalization and makes the system less transparent. Logic rules framed for small datasets have minimum number of rules that interns are very easy to understand and compare. One of the best, most flexible solutions is to frame fuzzy logic rules; however, fuzzy rule support is less for datasets with symbolic and nominal attributes. These alternative rules extraction systems are driven by similarity-based learning and are based on prototype rules. presented threshold rules algorithm, which uses a small number of highly precise ordered rules to extract threshold rules from data.
***Keywords*—** Rule based algorithm, Fuzzy logic, Classification algorithm, Threshold, CMAR, CBA, KNN

I. INTRODUCTION

To best predict the class, classification algorithms heavily rely on the threshold value K (the number of cluster). The threshold value for K is used by the KNN and K-means clustering algorithms to predict the class [1]. The other classification algorithms employ fixed sensitivity and specificity threshold values that are calculated by an algorithm and verified to predict the final class.[2] To accurately predict the class and lower the rate of misclassification, the choice of the ideal threshold value must be made. Decision threshold values have been the subject of numerous studies and analyses. The various threshold concepts and various rules for the suggested classification algorithm are covered in this paper.

II. THRESHOLD VALUE ON CLASSIFICATION ALGORITHM

The majority of classification methodologies use the threshold value in a variety of ways to determine the final class. Many classification algorithms predict the class using the threshold value and support and confidence values.[3] The threshold value must be compared with by the algorithm that predicts the final class using the support and confidence values.

The threshold value serves as a class boundary value. The accuracy of the classifier is improved by the classification algorithm KNN, which uses various modified threshold value as a key value. It is one of the most straightforward and widely used classification models, using threshold value to foretell the next-closest value. In contrast to most others, KNN does not require any training phases, making it a quick classification method. Using a distance metric like the Euclidean distance, k training samples are obtained for each test sample in this method.[4] Within these k samples, the test sample's class is determined by majority voting.

With support and confidence threshold values, the proposed algorithm is compared to rule-based algorithms like CMAR, CBA, and C4.5.[5] The implementations of these three classification algorithms—CMAR, CBA—on various medical datasets with fixed threshold values are covered in this section. The Support and confidence to predict the class are calculated by the Association rule-based algorithm. [6] How frequently the items appear in the database is indicated by their support. The number of times the if/then statements have been verified as true is indicated by confidence.

Equation 1 is used to calculate the support in the Association rule mining.

$$Support = occurrence\ of\ the\ instances\ /\ Total\ support \tag{1}$$

and the confidence is calculated for given x=> y using the equation 2

$$Confidence = occurrence\{y\}\ /\ occurrence\{x\} \tag{2}$$

The authors in [7] developed the new associative classification method known as CMAR, or Classification based on Multiple Association Rules, in 2001. The author of this algorithm used the confidence values and support threshold value to predict the class as CBA. The confidence difference threshold is set to 20%, and the database coverage threshold is set to 80%. The author disabled the cap on the number of rules for CBA and set the support threshold to 1% and confidence threshold to 50%. Other settings are left at default. It only reports the accuracy for the rule method because it is more accurate.

Many data sets from the UCI Machine Learning Repository [8] were tested by the author. Database coverage threshold and confidence difference threshold are two crucial CMAR parameters. The total number of rules chosen for classification is limited by these two thresholds. These two thresholds produced nominal accuracy when applied to the dataset, indicating that it was impossible to predict the ideal threshold values beforehand.

TABLE 1ACCURACY ON MEDICAL DATASET

Data Set	Attr#	Cls#	Rec	C4.5	CBA	CMAR
WisconsinBreast Cancer	10	2	699	95	96.3	**96.4**
Cleveland heart disease	13	2	303	78.2	**82.8**	82.2
Crx heart disease	15	2	690	84.9	84.7	**84.9**
Pima IndianDiabetes dataset	8	2	768	74.2	74.5	**75.8**
Heart diseasedataset	13	2	270	80.8	81.9	**82.2**
Hepatic	19	2	155	80.6	**81.8**	80.5

On a variety of medical datasets from the UCI repository, the table 1 displays the accuracy attained by three current rule-based algorithm models, CBA, CMAR, and c4.5, each with a static threshold value. In this study, a medical dataset with two resultant classes was used. On the binary class classification, all three algorithms were tested. The algorithms also make use of the predetermined support and confidence thresholds. The class is over when the rule set reaches the cutoff point. The algorithms work well and produce accurate classification results for two classes. The algorithms haven't used a dataset that yields multiclass performance and classification results.

The dynamic threshold value is introduced for the support value in our proposed algorithm and is implemented in the algorithm that supports both binary class and multiclass classifications. The accuracy of the complex rule set is higher than that of the existing rule-based classification algorithms that use static threshold values.

III. THREESHOLD VALUE FIXING PROBLEM

When the closest value to the threshold is obtained, the threshold value-based classification algorithm predicts the class. It is difficult to predict the class in a multiclass classification when two or more classes have the same nearest distance to the threshold value. The nearest neighbor concept is used by the k-NN. In our study, the rule-based classifier's threshold value is determined by the nearest neighbor. The optimum value is used to predict the class rather than the approximate value.

The threshold value is necessary for the classification algorithms that use support and confidence values to compare and accurately predict the class. In those algorithms, the support and confidence threshold values are predetermined by the user and are not altered as the algorithm is being run. The user-set threshold is regarded as static because it is constant. The classification accuracy will rise with the change in threshold value's percentage. The greatest value out of the n values is selected as the threshold value for the modified threshold value, which is dependent on the determination of the support factor for each class. The association rule's support and confidence equation is used to calculate the support factor, which results in the formation of the following equation 3.

$$Support\ Factor\ =\ number\ of\ factors\ satisfies\ the\ rule\ /\ total\ factors \quad (3)$$

And the support factor percentage is calculated using the equation 4.

$$Support\ percentage\ =\ Support\ factor/100 \quad (4)$$

The accurate threshold percentage should be set so that the classifier is as accurate as possible. Choosing and establishing an accurate threshold value is another difficult task in obtaining the best classification percentage.

The dataset, which has "m" attributes and "n" classes that need to be predicted, does not require that all "m" attributes be checked in order to predict all "n" classes. The classification time will be shortened by identifying the attributes associated with the particular class. Certain attributes do not need to be checked, and doing so will prolong the classification process. Only a small subset of the "m" attributes that support class C1 must be taken into account in order to predict class C1, and only a small subset of other attributes must be taken into account in order to predict class C2. Certain characteristics that support class C1 also support class C2, so those characteristics must also be considered when predicting class C1.

The number of attributes for each class will vary, and different numbers of attributes must be checked in order to predict each class. Additionally, the threshold value percentage used to determine the class in each instance will vary. Therefore, it is debatable whether the threshold value should be set as a constant. The support value with the closest value is predicted as the resultant class when the threshold value is fixed as a constant. Another issue arises when two or more classes have percentages that are close to the fixed threshold value, leading to a tedious class as a result. Example: Consider a multi-class problem where the threshold value is fixed at 80% and there are two classes, each with a percentage of 70% and 90%, and both classes are within the same distance of the threshold value. Therefore, predicting the resultant class becomes difficult. The concept of nearest value does not result in the best class prediction; instead, the best threshold value is required to produce an accurate class prediction.

Fixing a static threshold value will have an impact on the accuracy and performance of sensitive datasets. [9,10] The characteristics specific to those cases alone will be taken into account more than the other characteristics in order to determine the cause of a given case. Using any of the statistical techniques, the threshold values were established, and the fixed value is static. The algorithm checks each class' attributes and calculates its support counts when there are a total of two classes in the sample, C1, C2, and when the threshold value is fixed as some constant value "N%". If it reaches the threshold value "N%", the algorithm fixes the cause for the specific case as C1, otherwise it fixes the cause as C2. Fixing a static threshold value raises the wrong prediction rate when there are multiple classes (C1, C2, C3,..., Cn). When the attributes for each class vary in size according to its attributes, the mean value for each case must be calculated separately.

Setting the proper threshold value will help you predict the class. A difficult task is selecting an accurate threshold value for an algorithm to predict the class.[12] The threshold value has been set using a variety of methodologies. In some circumstances, the minimum requirements must be met in order to predict the class. Depending on the user constraint, that minimum value may need to be fixed. However, the minimum constraint does not always work. Particularly for medical datasets, the maximum support should be counted when predicting a record's class. When the minimum threshold is set, there is a chance that the class will be predicted incorrectly, which can result in misclassification and an increase in the misclassification rate. In order for multiclass classification to correctly predict the class, a dynamic threshold value is required.

Considering these limitations in our research, The threshold value is established by treating the threshold value as the maximum acceptable value rather than the minimum. Additionally, the algorithm will need to calculate that maximum satisfactory value repeatedly because it will vary for each record. The rule set is applied to the dataset, and for multiclass classification, the maximum acceptable value is calculated for each class and fixed as a threshold value to predict the class. The correctly predicted class for the test dataset is compared using the training dataset as a prototype. Here, we're using the p-rule as our classification basis. However, the algorithm uses a dynamic threshold value and includes both P-rules and f-rules.

IV. DYNAMIC THRESHOLD VALUE

The nature of medical data sets is more delicate. It's critical to predict and categories the root causes of each disease. The classes of medical datasets are predicted using the rule-based algorithm. For a rule-based algorithm to perform an accurate classification, a threshold value is required. When a threshold value for a classification is fixed statically, the algorithm declares the classification complete when it reaches the fixed value. For categorization into binary classes, it works well. The predicted outcome is impacted by fixing a static threshold value for the dataset with "N" classes. For medical data sets with multiple classes, a dynamic method of setting threshold values is especially important.

By setting the dynamic threshold value, the performance of classification is improved and the number of wrong classifications is cut down. The threshold values for sensitive data are modified periodically for each record. To accurately predict the class, a rule-based algorithm with a dynamic threshold value is required. The modified RBA algorithm is applied in two stages; in the first stage, the dataset is preprocessed using the discretization concept to reduce dataset complexity.

In the second phase, the modified RBA with predefined rules is put into use for classification. On various medical datasets, we implement the Rule Based Classification Algorithm with Dynamic Threshold Value in this paper, and its performance is assessed. Our implementation demonstrates that, on various medical datasets, the enhanced RBA with a dynamic threshold value outperforms other approaches.

When using a rule-based algorithm, the number of instances that satisfy the given rule is counted after the rule is applied to the data set. Here, when the threshold value is fixed as a constant, it ends the class when it reaches that value, which causes misclassification. The threshold value cannot be fixed as a static one when sensitive data uses multiple rules to predict multiple classes when using rule-based classification. whenever the threshold value is switched. As a result, the proposed rule-based algorithm applies multiple rules to the test data to determine the percentage that each class perceives. For each situation, a different percentage is received. Each record results in changes to the threshold value, and the class is predicted using Euclidean distance metrics.

When a rule-based algorithm is used for multiclass classification, it predicts that class C1 will come out on top with a threshold value of 60%. This threshold value serves as the first instance's cutoff value, and all other classes receive percentages that are lower than C1's threshold value. The algorithm predicts that the resultant class of the second instance will be c1 with a support factor value of 70% or 50%, which is also the instance's threshold value. Less than the predicted value of the support factor will be received by the other n-1 classes. The threshold value was either higher or lower than the previous threshold value. The maximum support factor is fixed as a threshold value and varies for each instance. Here, the threshold value is established in relation to the percentage of n-1 classes with satisfactory factors.

V. RULE GENERATION

The proposed algorithm employs a dynamic threshold value and is designed using the p-rule and f-rule. There are numerous rule-based algorithms, such as CBA and CMAR, which use various kinds of rules and are linked to association and decision rules, respectively. The suggested algorithm generates rules using a fuzzy rule (F-rule) to handle complex queries and a proto type to check for similarity. To accurately predict the class using our algorithm, we also use the distance function.

The dynamic threshold-based classification algorithm that is proposed is made with the help of a set of rules. The rules are developed by researching already-existing rules. Different kinds of rules are employed to express various knowledge types. The Threshold Rules Decision List Algorithm, which supports binary classes, is the foundation of our research. The rule iteratively tests the dataset and fixes the threshold value to be constant. In our proposed algorithm, the standard rule sets are applied to the chosen dataset for multiclass classification, and the threshold value is instantly calculated for each class.

Algorithm for rule generation:

Input: D, a data set class-labeled tuples; Attvals, the set of all attributes and their possible values.

Output: A set of IF-THEN rules.

Method:

Step 1: Rule set = {}; // initial set of rules learned is empty
Step2: For each class c do
Step2.1: Repeat Rule = Learn One Rule (D, Attvals, c);
Step 2.1.1: remove tuples covered by Rule from D;
until terminating condition;
Step2.2: Rule set = Rule set + Rule; // add new rule to rule set
End for
Return Rule Set;

VI. CONCLUSION

This paper explains the various rules that make up the rule-based algorithm and the significance of threshold values for classification. The difficulties with using the nearest neighbor concept and static threshold values, as well as the significance of dynamic threshold values. By setting the dynamic threshold value, the performance of classification is improved and the number of wrong classifications is cut down. The threshold values for sensitive data are modified periodically for each record. To accurately predict the class, a rule-based algorithm with a dynamic threshold value is required. The calculated threshold value is then used to draw conclusions about the resultant class.

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