대한산업공학회/한국경영과학회 ’98 춘계공동학술대회 논문집.1998 년 4 월 24-25 일. 경성대학교:Session C 05.2

A Case-based Reasoning Approach for Corporate Bond Rating

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ABSTRACT

Case-based reasoning is a problem solving technique by re-using past cases and experiences to find solutions to problems. The central tasks that CBR methods have to deal with are to identify the current problem situation, find a past case similar to the new one, use that case to suggest a solution to the current problem, evaluate the proposed solution, and update the system by learning from this experience. Among these tasks, one of the critical issues in building useful CBR system lies in indexing of cases that supports the retrieval of relevant cases to the problem.

This paper investigates the effectiveness of integrated approach using induction techniques to case indexing process for business classification tasks. We suggest this approach as a unifying framework to combine general domain knowledge and case specific knowledge. The proposed approach is demonstrated by applications to corporate bond rating.

1. INTRODUCTION

Case-based reasoning (CBR) is a problem solving technique that is fundamentally different from other major AI approaches. Instead of relying on making associations along generalized relationships between problem descriptors and conclusions, CBR is able to benefit from utilizing the specific knowledge of previously experienced problem situations. A new problem is solved by finding a similar past case and reusing it in the new problem situation.

Wide range of applications of CBR have been reported (Brown and Gupta, 1994; Chi, Chen and Kiang, 1993; Hansen, Meservy and Wood, 1995; Morris, 1994; Mechitov, Moshkovich, Olson and Killingsworhth, 1995; O’ Roarty, Patterson, McGreal and Adair, 1997; Riesbeck and Schank, 1989), including business classification for decision making such as bond rating (Buta,1994) and bankruptcy prediction (Bryant,1997).

The central tasks that CBR methods have to deal with are to identify the current problem situation, find a past case similar to the new one, use that case to suggest a solution to the current problem, evaluate the proposed solution and update the system by learning from this experience (Kolodner, 1993; Riesbeck and Schank, 1989; Slade, 1991).

Among these major tasks, one of the major issues lies in the retrieval of appropriate cases (Hansen, Meservy and Wood, 1995). An index used to retrieve cases from memory may fail even if there is a relevant case in memory (Kolodner, 1991). This happens when the index does not correspond to the one used to index the case. The indexing problem (Kolodner, 1993) refers to the task of storing cases for effective and efficient retrieval.

In this paper, we discuss implementation of effective indexing methods to solve the classification tasks. Our particular interest is an integrated approach using induction technique and CBR to retrieve more relevant cases. This approach aims at unifying case-specific and general domain knowledge within the system. The proposed approach is demonstrated by applications to corporate bond rating.

This paper is organized as follows. The following section provides a brief description of prior research on corporate bond rating studies. Section 3 describes the characteristics of indexing and retrieving methods of CBR. Section 4 explains the integrated approach for effective CBR system. Section 5 and 6 report the experiments and empirical results of corporate bond rating application. Final section discusses conclusions and future research issues.

2. PRIOR RESEARCHES ON BOND RATING

Corporate bond rating informs the public of the likelihood of an investor receiving the promised principal and interest payments associated with the bond issues. Bond ratings characterize the risk for the investments and affect the cost of borrowing for the issuer, and are rated by independent rating agencies.

Numerous bond rating studies have traditionally used statistical techniques such as multiple discriminant analysis (Baran, Lakonishok and Ofer, 1980; Belkaoui, 1980; Pinches and Mingo, 1975), regression (Horrigan, 1996; Pogue and Soldofsky 1969; West, 1970), probit (Kaplan and Urwitz, 1979) and logit (Ederington, 1985) models.

Recently, however, a number of studies have demonstrated that artificial intelligence approaches such as neural networks (Dutta and Shekhar, 1988; Kwon, Han and Lee, 1997; Maher and Tarun, 1997; Singleton and Surkan, 1995), rule-based system (Kim and Lee, 1995) and case-based reasoning (Buta, 1994; Shin, Shin & Han, 1997) can be alternative methodologies for business classification problems. Among these studies, Kwon *et al*. (1997) and Shin *et al*. (1997) developed corporate bond rating model using Korean bond rating data.

Kwon *et al*. (1997) used ordinal pairwise partitioning (OPP) approaches to back-propagation neural networks training for corporate bond rating prediction. The main idea of the OPP approach is to partition the data set in the ordinal and pairwise manner into the output classes. Experimental results show that the OPP approach has the highest level of accuracy (71%-73%), followed by conventional neural networks (66%-67%) and multiple discriminant analysis (MDA) (58%-61%).

Shin *et al*. (1997) applied case-based reasoning using inductive indexing method. Despite the optimistic hope that inductive indexing methods can improve the effectiveness of case reasoning resulting higher classification accuracy, the experimental results are rather disappointing. Although the proposed model failed in respect to the classification accuracies, the exercise has suggested some valuable insights. That is, the success of the case-based reasoning system using inductive indexing approach largely depends on the appropriateness of induction trees, underlining the necessity of optimizing decision trees,

3. CASE INDEXING AND RETRIEVING

Case indexing involves assigning indices to cases to facilitate their retrieval. Indices organize and label cases so that appropriate cases can be found when needed. In building case-based reasoning systems, CBR community proposes several guidelines for choosing indexes for particular cases: (1) indexes should be predictiveness, (2) indexes should be abstract enough to make a case useful in a variety of future situation, (3) indexes should be concrete enough to be recognizable in future cases, and (4) prediction should be useful (Kolodner, 1991; 1993). Both manual and automated methods have been used to select indices. Choosing indices manually involves deciding the purpose of case with respect to the aims of the reasoner and deciding under what circumstances the case may be useful.

The second issue of indexing cases is how to structure the indices so that the search through case library can be done efficiently and accurately. Given a description of a problem, a retrieval algorithm, using the indices in the case-memory, should retrieve the most similar cases to the current problem or situation. The retrieval algorithm relies on the organization of the memory to direct the search to potentially useful cases.

Indices can either index case features independently for strictly associative retrieval or arrange cases from the most general to the most specific for hierarchical retrieval (Brown and Gupta, 1994). There are three approaches to case indexing: nearest-neighbor, inductive, and knowledge-guided (Barletta, 1991).

3.1 Nearest-neighbor indexing

The nearest-neighbor approach involves the assessment of similarity between stored cases and the new input case, based on matching a weighted sum of features. One of the most obvious measures of similarity between two cases is the distance. A numeric evaluation function measuring distance taking into account of importance features to compute the degree of match in retrieval is as follows:

$$DIS_{ab} = \sqrt{\sum_{i=1}^{n} w_i \times (f_{ai} - f_{bi})^2}$$

where DIS is the matching function using Euclidean distance between cases, n is the number of features, and w_i is the importance weighting of a feature i .

Basic steps of nearest-neighbor retrieval algorithms are quite simple and straightforward. Every feature in the input case is matched to its corresponding feature in the stored case, and the degree of match of each pair is computed using matching function. Based on the importance assigned to each dimension, an aggregate match score is computed. Ranking procedures order cases according to their scores, and higher scoring cases are used before lower scoring ones. Figure 1 represents the nearest-neighbor matching algorithm

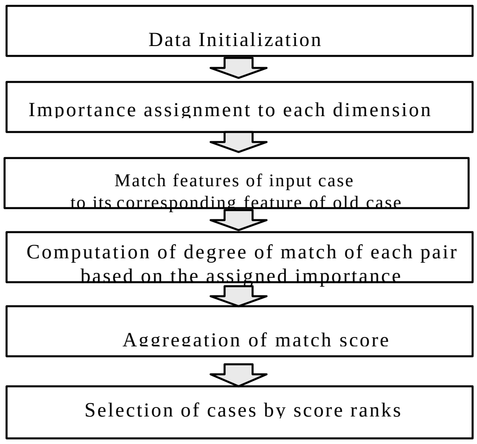

Figure 1. Nearest-neighbor matching algorithm

This approach is preferred to use if the retrieval goal is not well-defined or if few cases are available (Barletta, 1991). One of the major problems of this approach is to determine global feature weights among attributes. Another limitation of this approach includes problem in converging on the correct solution and retrieval times. In general the use of this method leads to the retrieval time increasing linearly with the number of cases.

3.2 Inductive indexing

When a case library is large, there is a need to organize cases hierarchically so that only some small subset needs to be considered during retrieval. This subject, however, must be likely to have the best-matching or most useful cases in it (Kolodner, 1993). In hierarchical retrieval, cases are stored in a decision tree where the top node contains common properties of all cases while nodes further down the tree are indexed based on their differences with other cases. An intermediate node represents a general description of cases under that particular node (Brown and Gupta, 1994).

Several inductive clustering methods can be used to do this job. Induction algorithms such as ID3 (Quinlan, 1986) and CART (Classification And Regression Trees), determine which features do the best job in discriminating cases and generate a tree type structure to organize the cases in memory. This approach is useful when a single case feature is required as a solution and where that case feature is dependent upon others.

3.3 Knowledge-guided indexing

Knowledge-guided indexing applies existing domain and experimental knowledge to locate relevant cases. Although this method is conceptually superior to the other two, knowledge-guided indexing is difficult to carry out since such knowledge often cannot be successfully and exhaustively captured and represented. Therefore, many systems use knowledge-guided indexing in conjunction with other indexing techniques (Barletta, 1991; Brown and Gupta, 1994). Nearest-neighbor retrieval using feature weights assigned by experts' opinions can be one example.

4. INTEGRATING INDUCTION TECHNIQUE AND CASE-BASED REASONING

Inductive learning and case-based reasoning are classification techniques that can be applied in financial decision making. Induction and case-based reasoning techniques are compared by considering that the first technique makes direct use of past experience at the problem solving stage while the second one only uses an abstraction of the cases. Induction compiles past experiences into general knowledge, which are then used to solve problems. Case-based reasoning directly interprets past experience.

The integration of induction technique and case-based reasoning reaps the benefits of both systems for the following reasons. First, we can retrieve more relevant case through generalized domain knowledge derived by induction technique. CBR has some drawbacks in that the technique ignores general knowledge for the domain. This means useful information might be forgotten. Since induction extracts explicit knowledge from the data, CBR can be benefited from integrated approach. Second, the integrated approach can enhance efficiency of the system because only some small subset needs to be considered during retrieval.

We integrate inductive clustering technique and case-based reasoning by using inductive indexing scheme.

As the first step, we build a decision tree for case indexing. A decision tree is built upon a database of training cases. For example, the partitioning procedure of ID3 uses a preference criterion based on the information gain. At each node in the induction tree, the information gain is evaluated for all the attributes that are relevant and the one which yields the highest increase is selected.

The success of inductive indexing approach, however, largely depends on the appropriateness of decision trees for case retrieval (Kolodner, 1993; Shin, Shin & Han, 1997). To find an optimal or near optimal decision tree, we apply four different stopping conditions for the trees. The stopping criterion denotes the maximal depth of the tree, defining the maximal number of levels an induction tree shall have. Figure 2 illustrates the levels of depth of decision tree.

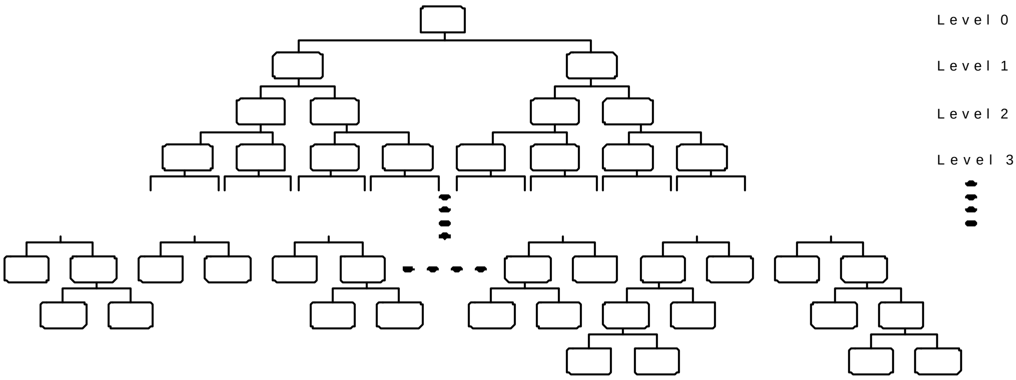

Figure 2. Depths of the decision tree

First model integrates induction tree which has 3 levels of depth and case-based reasoning by applying nearest-neighbor at the end of induction tree. This allows to determine the most similar cases to the current situation, and to choose the most probable value in this subset of cases. Second, third and fourth models follow the same procedure except induction trees have 5, 7 and 9 levels of depth, respectively. As a partitioning criterion, the information gain measure based on Shannon’ s entropy (Shannon and Weaver, 1947) is used.

5. DATA AND VARIABLES

The sample data consists of financial ratios and corresponding bond ratings of Korean companies. The ratings have been performed by National Information and Credit Evaluation, Inc., one of the most prominent bond rating agencies in Korea. The total sample available includes 3,886 companies whose commercial papers have been rated from 1991 to 1995. Credit grades are defined as outputs and classified as 5 grade groups (A1, A2, A3, B, C) according to credit levels. Table 1 shows the organization of data set.

Table 1. Number of companies in each rating

Ratings	Number of cases	%
A1	260	6.7
A2	833	21.4
A3	1,314	33.8
B	1,406	36.2
C	73	1.9
Sum	3,886	100.0

Table 2. Definition of variables

Variable	Definitions
X1	Firm classification by group (conglomerate) types
X2	Firm types
X3	Total assets
X4	Stockholders' equity
X5	Sales
X6	Year after founded
X7	Gross profit to sales
X8	Net cash flow to total assets
X9	Financial expenses to sales
X10	Total liability to total asset
X11	Depreciation to total expenses
X12	Working capital turnover

We apply two stages of input variable selection process. At the first stage, we select 27 variables (23 quantitative / 4 qualitative) by factor analysis, 1-way ANOVA (between input variable and credit grade as output variable) and Kruskal-Wallis test (for qualitative variables). In the second stage, we select 12 financial variables

(10 quantitative / 2 qualitative) using stepwise method of MDA to reduce the dimensionality. The input variable selection approach is to select input variables satisfying the univariate test first, and then select significant variables by stepwise method for refinement. In choosing qualitative variables, the four variables have been initially selected. However, audit opinion and audit firm are excluded by the expert’s opinion. Two selected qualitative variables are firm classification by group (conglomerate) types and firm types. We classify conglomerates into five categories include top-ten conglomerates, top-twenty conglomerates, top-thirty conglomerates, top-forty conglomerates and non-conglomerates. Four types of firms are listed, registered, external audit and ordinaries. Table 2 illustrates selected variables for this study.

Each data set is split into two subsets, a reference set and a validation (holdout) set. The reference data are used to form a decision tree to index cases and also as a case base for retrieval. The validation data are used to test the model's results with the data which have not been used to develop the system. The number of the reference cases and the validation cases are 3,486 and 400, respectively.

6. EXPERIMENTS AND RESULTS

To study the effectiveness of integrated approach for case indexing in the context of the corporate bond rating problem, the results obtained are compared with those of other indexing techniques such as CBR-pure model and CBR-expert model. The CBR-pure model uses a nearest-neighbor algorithm that has equal weights among attributes. The CBR-expert model applies important weights assigned by expert.

Table 3. Importance weights assigned by experts

Var.	Exp (1)	Exp (2)	Exp (3)	Exp (4)	Exp (5)	Assigned value	Var.	Exp (1)	Exp (2)	Exp (3)	Exp (4)	Exp (5)	Assigned value
X1	0.8	0.8	0.8	0.8	0.4	0.72	X7	0.6	0.8	0.4	0.8	0.8	0.68
X2	0.4	0.2	0.4	0.6	0.4	0.40	X8	0.8	0.6	0.6	0.8	0.8	0.72
X3	0.8	0.8	0.8	1.0	0.6	0.80	X9	0.8	0.8	0.6	0.8	0.8	0.76
X4	1.0	0.8	0.6	1.0	1.0	0.88	X10	0.8	0.8	0.6	1.0	0.8	0.80
X5	0.8	0.6	0.6	1.0	1.0	0.80	X11	0.2	0.4	0.4	0.8	0.6	0.48
X6	0.6	0.8	0.8	0.8	0.6	0.72	X12	0.6	0.8	0.4	0.8	0.8	0.68

For this experiment, we have experts designate importance of an attribute by assigning the equivalent of 5 qualitative values by interview. We have selected 5 experts, three from bond rating department of a credit rating agency, and two from credit analysis department of a commercial bank. The work experience of selected experts related to credit analysis ranged from 2 to 8 and half years while the average of experience is 4 years and 2 months. Five qualitative values are “most important,” “very important,” “important,” “less important,” and “ignore” which are associated with numbers for computation as 1.0, 0.8, 0.6, 0.4, and 0.2, respectively. Table 3 shows the assigned importance to each attribute by experts. Importance values are ranged from 0.4 to 0.88.

As mentioned above, we apply four predetermined stopping conditions. Integrated (1) model applies the decision tree which has 3 levels of depth. Integrated (2), (3) and (4) models follow the same procedure except the decision trees have 5, 7 and 9 levels of depth, respectively. Table 4 represents different stopping conditions and corresponding figures of the decision trees. The decision trees we employ are built by packaged software KATE^{TM}.

Table 4. Figures depend on different stopping conditions

Model	Stopping condition (depth)	Number of nodes	Number of leaves	Number of cases per leaf	Average number of questions	Average depth
Integrated (1)	3	15	8	435.8	2	3
Integrated (2)	5	63	32	108.9	3.4	5
Integrated (3)	7	229	115	30.3	4.7	6.9
Integrated (4)	9	511	256	13.6	5.5	8.4
Full (no condition)		1,491	746	4.67	6.9	11.8

As shown in Table 4, the important figures of decision trees are dramatically affected by different stopping conditions. For example, the number of leaves increases from 8 to 746 depends on the depth of tree.

Since the number of leaves corresponds to the number of inductive clusters for case organization, 8 and 746 leaves denote 8 and 746 clusters for cases, respectively. Since the main role of induction in this context is to extract general domain knowledge from database, we can easily expect that the higher number of clusters does not ensure the effective case-based model.

Table 5 represents the comparison of the results of the classification techniques applied for this study. Each cell contains the accuracy of the various classification techniques by classes. The results of popular classification techniques such as multiple discriminant analysis (MDA), ID3 and back-propagation neural networks (BPN) are also presented as benchmarks to verify the applicability of proposed model to the domain.

Table 5. Classification accuracies (%)

Methods		A1	A2	A3	B	C	Average
MDA		57.7	69.8	58.3	55.0	77.8	60.0
ID3		65.4	55.8	47.5	72.9	33.3	59.0
NN	PNN	80.8	72.1	52.5	57.9	22.2	59.8
	BPN	46.2	65.1	61.9	77.9	0.0	65.8
CBR	Pure	65.4	66.3	58.3	66.4	0.0	62.0
	Expert	69.2	65.1	58.3	63.6	0.0	61.0
	Integrated (1)	84.6	74.4	64.7	70.7	22.2	69.3
	Integrated (2)	80.8	72.1	66.9	72.9	22.2	70.0
	Integrated (3)	76.9	62.8	63.3	73.6	11.1	66.5
	Integrated (4)	61.5	61.6	58.3	71.4	11.1	62.8

Among the techniques, the integrated models have the highest level of accuracies (Integrated (2): 70.0%, Integrated (1): 69.3%) in the given data sets, followed by back-propagation neural networks (65.8%) and CBR-pure model (62.0%). MDA and ID3 have similar levels of classification accuracy. As we expected, the classification accuracies are affected by the depth of decision trees. Figure 3 shows corresponding accuracies depend on the depth of the trees.

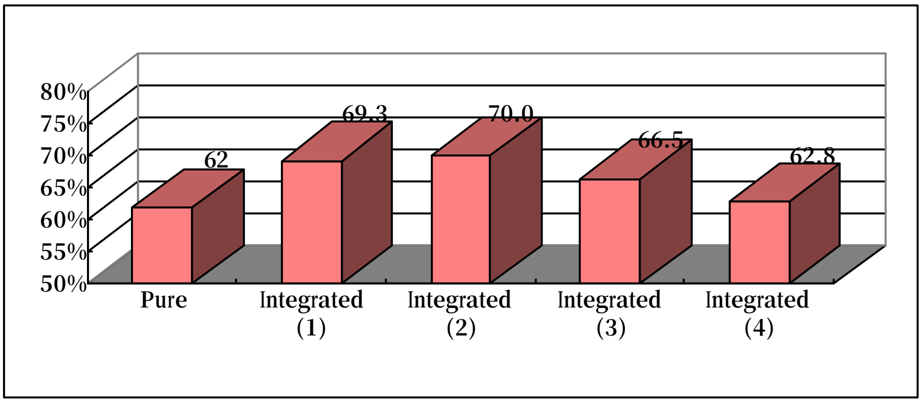

Figure 3. Classification accuracies by integrated models (%)

A comparison of integrated models indicates that higher level of depth in induction does not guarantee higher performance for integration. The accuracies of integrated (3) and (4) models decrease as the depth of decision trees increases. This result underlines the necessity of optimizing decision trees to apply in a case-based retrieval and not simply leaving it to the induction technique itself to do the job.

We use the McNemar tests to examine whether the predictive performance of integrated approach is significantly higher than that of other techniques. McNemar test is a non-parametric test of the hypothesis that two related dichotomous variables have the same means. This test is useful for detecting changes in responses due to experimental intervention in 'before and after' designs using the chi-square distribution. Since we are interested in the correct prediction of cases, the measure for testing is the classification accuracy rate (the number of correct classification from the number of whole holdout samples). Table 6 shows the results of McNemar tests to compare the classification ability between benchmark models and integrated model (2) using decision tree which has 5 levels of depth for holdout samples.

Table 6. McNemar values for the pairwise comparison of performance between models

	ID3	NN-PNN	NN-BPN	CBR-Pure	CBR-Expert	CBR-Integrated (2)
MDA	0.050[a]	0.000	5.694 (**)	0.298	0.052	9.750 (***)
ID3	-	0.024	4.305 (**)	0.785	0.318	12.664 (***)
NN-PNN	-	-	3.947 (**)	0.576	0.108	13.675 (***)
NN-BPN	-	-	-	1.351	2.063	1.869
CBR-Pure	-	-	-	-	0.100	8.390 (***)
CBR-Expert	-	-	-	-	-	8.144 (***)

[a.] Chi-square values * significant at 10% ** significant at 5% *** significant at 1 %

The result shows the integrated model (2) performs significantly better than every benchmark model proposed for this study except back-propagation neural networks at a 1% significance level. Based on the results, we conclude that the integrated approach using induction is effective, enhancing the overall classification accuracy of the case-based system, for the application domain.

We also investigated the effect of number of cases retrieved in nearest-neighbor retrieval stage. The results of integrated model (2) by different number of nearest-neighbors are summarized in Table 7 and Figure 6. Varying numbers in the first row of the table denote the number of nearest neighbors retrieved. We determine the classification outcome of multiple cases retrieved by frequency measure. The results indicate that classification accuracies are affected by the varying number of cases retrieved to solve the problem. Although it is difficult to determine the optimal number of cases to retrieve from this experiment, we can see the fact that there are better alternatives than the single nearest-neighbor for problem solving.

Table 7. Classification accuracies depend on number of cases retrieved (%)

	1	2	3	4	5	6	7	8
A1	80.8	80.8	68.0	65.4	65.4	61.5	57.7	57.7
A2	72.1	72.1	69.9	70.9	69.8	73.3	73.3	74.4
A3	66.9	66.9	65.2	64.0	67.6	64.7	64.7	65.5
B	72.9	72.9	81.8	82.1	81.4	79.3	77.9	78.6
C	22.2	22.2	22.2	22.2	11.1	11.1	11.1	11.1
Avg.	70.0	70.0	71.2	71.0	71.5	70.3	69.5	70.3

7. CONCLDING REMARKS

This paper examined the potential effectiveness of using induction technique to support case-based reasoning for classification tasks. In this approach, induction technique is used to cluster and organize cases retrieve case efficiently and effectively. Our experimental results have shown that this approach increases overall classification accuracy rate significantly.

Based on the results, we conclude that knowledge acquired by problem domain supports retrieval of useful case to solve the problem. Induction technique provides general knowledge for the application domain, and CBR extracts case-specific knowledge through case retrieving. The experimental results of bond rating problem support that this integration reaps the benefits of both techniques.

Our study has a few limitations that needs further research. First, the determination of decision trees using the different stopping conditions has a critical impact on the performance of the system. However, we did not suggest theoretically sound procedures to determine optimal stopping condition include depth and criterion itself. We plan to find general method to determine stopping conditions for future research. This includes the issue of more appropriate stopping criterion than the depth of trees such as information gain measure.

The second issue for future research relates to the use of different outcomes derived from multiple nearest-neighbors. We used the closest neighbor as a final outcome in this paper. However, as shown in the results, a combining algorithm that can lead to the final decision is desirable for the system.

The aim of integrating different techniques is to make more powerful and efficient systems by taking advantage of the strength of each technology. Therefore, developing more effective methods using synergistic integration is another research issue for the future.

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