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Label Dependency Elimination in Multi-Label Classification Based On Feature and Teacher Learning Optimization

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Abstract: The classification and categorization is major issue in multi-features based data. As the classification and categorization of multi-features data are used multi-label classifications. The multi-label classification technique used the similarity based features selection process. In this paper, we proposed the feature optimization based multi-label classification. For the optimization of features used teacher learning based optimization technique. The teacher learning based optimization technique is basically based on dynamic iteration population algorithm and it reduces the unwanted and distinct feature of data for the process of classification. The modified algorithm implemented in mat lab software and used some reputed dataset for the evaluation of performance.

Keywords: Data Mining, MLC, Feature Optimization, TLBO

I. INTRODUCTION

The multi-level characterization procedure is extremely mind-boggling issue in information mining process. The procedure of multi-level arrangement system joined with bunching and order handle. The characterization strategy fell and upgraded for various level of highlight choice process. The procedure of highlight determination assumes an essential part in multi-class grouping [1]. In multi-class characterization prepare utilized component change cum highlight determination handle. The differences of highlight instigated an issue of highlight determination. Presently a day's different creators and analyst utilized component determination cum include streamlining strategy for the multi-level arrangement and multi-level order. For the change of order and grouping proportion utilized distinctive bunching and characterization system [2]. The real issue in multi-mark content classification is similitude measure of class and qualities esteem. For that change utilized different component choice based technique. Various types of machine learning calculations, for example, the KNN, support vector machine, and strategic relapse techniques, have been proposed to determine such order issue, and have accomplished a palatable level of grouping [3, 4].

Rather than that some certifiable issues, every example could be connected with numerous classes at the same time. The procedure of arrangement method partitioned into three segments, in first segment plan a learning procedure, in second area outline the testing stage and in conclusive segment plan the application stage. The classifier developer worked amid the learning stage [5, 6]. Classifier is a machine learning tool where the target attributes is categorical regression. The target attribute is continuous numeric value. It might be as order standards, a choice tree, or a numerical equation. The major challenges of the machine learning approach to text classification is how to translate the textual information into the features that eventually can be used by a machine learning algorithm [7,8]. In practice just using each word as a separate feature already works quite well. However, most approaches will generate an enormous number of features, which not all machine learning algorithms can handle well. In order for them to work, only the most promising features are selected to feed to the algorithm. The utility and diversity of multi-level classification technique invite different authors and scientist for the improving the classification ratio and validation of application of multi-level classification technique. Feature selection and feature optimization play an important role in multi-level classification technique [9, 10]. As long as the optimization and selection of feature different authors are used fuzzy logic, neural network and some other optimization technique. In this paper, teacher learning based optimization and feature classification process used. The rest of paper describe in section II feature optimization. In section III. Discuss proposed algorithm. in section IV discuss experimental result analysis and finally discuss conclusion and future work.

II. RELATED WORK

In 2011, Zhihua Wei et. al. The experiments over public data set demonstrate that the proposed methods has highly competitive performance with several well-established multi-label classification algorithms. They implement a

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prototype system named TJ-MLWC based on the proposed algorithm, which acts as an intermediate layer between user and a commercial Internet Search Engine, allowing the search results of a query displaying by one or multiple categories. Testing results indicate that our prototype improves search experience by adding the function of browsing search results by category [3].

In 2011, Hang Li et. al. gives an introduction to learning to rank, and it specifically explains the fundamental problems, existing approaches, and coming work of learning to rank. Several learning to rank methods using SVM techniques are described in details. Learning to rank can be employed in a wide variety of applications in Information Retrieval (IR), Natural Language Processing (NLP), and Data Mining (DM). Typical applications are document retrieval, expert search, definitions search, collaborative filtering, questions answering, key-phrase extraction, document summarization, and machine translation [4].

In 2011, Xin Li et. al. The resulting optimization problem can be solved efficiently applying an iterative procedure with alternating steps, while closed-form solutions exist for one major step. neighbor's labels are more credible candidates for a weighted KNN-based strategy, and then assigns higher weights to those candidates when making weighted-voting decisions. The weights can then be determined by using a generalized pattern search technique [2].

In 2012, Purvi Prajapati et. al. introduces the task of multi-label classification, methods for multi-label classification and evolution measure for multi-label classifications. Multi-label classification methods are increasingly compulsory by modern applications, such as text classification, gene functionality, music categorization and semantic scenes classification. The number of class labels is predicted for each instance [7].

In 2014, Prema Nedungadi et. al. KNN works well in feature space and multiple regression works well for preserving label dependent information with generated models for labels. Their classifier incorporates feature similarity in the feature space and label dependency in the label space for prediction. It has a wide range of applications in various domains such as in information retrieval, query categorization, medical diagnosis and marketing. The results obtained with various multi-labeled dataset justify our method [1].

In 2014, Yang Zhou et. al. introduced a novel concept of vertex-edge homophile in terms of both vertex labels and edge labels and transform a general collaboration graphs into an activity-based collaboration multi graph by augmenting its edges with class labels from each activity graphs through activity-based edge classification. Finally, they design an iterative learning algorithm, AEC class, to dynamically refine the classification results by continuously adjusting the weights on different activity-based edge classification schemes from different activity graphs, while constantly learning the contribution of the structure affinity and the label vicinity in the unified classifier [5].

In 2014, Yaqing Wang et. al. described to construct a hyper graph for exploiting the high-order label relations and in current edge a novel framework for multi-label classification named Hyper Graph Canonical Correlation Analysis (HCCA). This idea is based on canonical correlation analysis, and it further takes into account the high-order label structure information via hyper graph regularization. Thus, the label relations can be better respected both globally by the normalized similarity matrix of CCA and locally by the normalized hyper graph Laplacian in a unified framework [15].

III. FEATURE OPTIMIZATION

Now the process of feature selection used teacher learning based optimization technique. The teacher learning optimization iteration based algorithm developed by RAO in 2011[11]. The Teacher learning based algorithm works on the scenario of class room teaching. In scenario of class learning tow factor are involved one is teacher and other is student. The process of learning estimates the capacity of learner and these learning satisfy the condition of teacher and that learner is optimal solution of class. The learner proceeds in optimal categorized satisfied the given constrains function decided by the teacher factor. The TLBO algorithm proceeds in two phases. The first phase of algorithm works in Teacher and second phase in student [12].

The processing of feature selection used some parameter for the processing of TLBO algorithm. N is the size of feature space and D is the value of selection of D during the processing of feature in terms of Students. For the processing of data consider the maximum iteration that is ITR.

Begin

1. Initialized the population of TBLO algorithm in terms of feature space as learner and student

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$$x^{0}_{(i,j)}=x_j^{min} + rand \times \left(x_j^{max} - x_j^{min}\right) \ldots\ldots\ldots\ldots\ldots(1)$$

Here rand function distributes the value of (0,1) for maximum and minimum generation of new population. The new generation of population describe as

$$X_{(i)}^{g} = \left[x_{(i,1)}^{g}, x_{(i,2)}^{g}, \ldots\ldots\ldots\ldots.. x_{(i,j)\ldots\ldots\ldots,x_{(i,D)'}^{g}}^{g}\right] \ldots\ldots\ldots\ldots\ldots..(2)$$

2. Estimate the mean value of new generation of learner in given feature data. the value of mean of new generation is estimate as

$$M^{g} = \left[m_1^{g}, m^{g}_{2,\ldots\ldots\ldots\ldots\ldots m_j^{g,\ldots\ldots\ldots\ldots m_D^{g}}}\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(3)$$

4. Estimation of teacher factor for the processing of new generation of learner. The teacher value of new generation of population. If the value of teacher factor is either 1 and 2. If the value of TF is 1 there is no change in new population else new population is generated. The estimate of teacher factor as

$$Xnew^{g}_{(i)=X^{g}_{(i)+rand}} \times \left(X^{g}_{Teacher} - TFM^{g}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

5. Calculate the value of teacher factor as given equation

$$T_{F=round\ [1+rand\ (o,1)\{2--1\}]} \ldots\ldots\ldots\ldots\ldots\ldots.(5)$$

6. Estimate and correlation of new learner with pervious learner feature data for the processing of learning. And generation of new population [11,12].

$$Xnew^{g}_{(i)=\{x_i^{g} + rand \times (X_i^{g} - X_r^{g})\ if\ f(X_i^{g}) < f(X_r^{g})}$$
$$X_i^{g} + rand \times (X_r^{g} - X_i^{g})\ otherwise \ldots\ldots\ldots(6)$$

7. If the generation process of new population is stop then iteration is terminated.

IV. PROPOSED TECHNIQUE

The proposed algorithm of multi-label classification for data categorization. For the reduction of feature of multi – attribute data are reducing by TLBO algorithm. The TLBO algorithm reduces the features set and passes through the classifier. For the classification of data used KNN classifier [13,14].

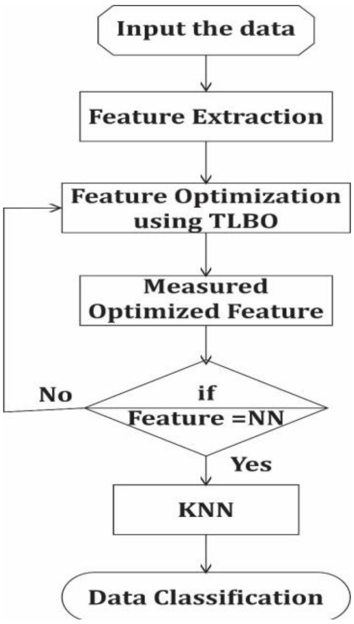

Figure 1: Proposed Model

In the flow chart, we insert the data in the initial point. With the help of feature extraction, we extract the insert data. After the extraction, we optimized the data using teacher learning based optimized. After the optimization, we measure it and get a condition where feature=NN that condition is yes then proceed forward otherwise get a backward stage of TLBO. Finally, the KNN crossover, we get the data classified.

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The KNN classifier used features reduction process for elimination of label dependency. The process of algorithm describes below.

1. Input the selected feature from TLBO in KNN
2. The selected value of features F mapped in relation of Fi$\in R^{d}$ here d is size of feature set.
3. Sampling of input features vector for the measuring similarity of features
   sim features$= \sum_{i=1}^{m} \sum_{j=1}^{n} sim(Xi,xj)/m * k$
4. Process the number of attributes for the classification.
5. Measure the value of estimate reduces features for the process of classification
   $x(t) = w0 + \sum_{j=1}^{total\ data} wj \exp\left(\frac{-(total - xj)}{\sigma^2}\right)$ This NN attribute of classifier
6. Decide the class after elimination of features estimate final C data for training of class
7. Lo=SimFet$\frac{1}{p}\sum_{i=1}^{p} min\,(FX - Fy)$ where Lo is training parameter of NN.
8. Assigned the trained feature as label c1, c2,……………cn
   If class level is C=¢ then terminated the process there is no features for the classification
9. Else
   Find multi-level class
   C=T(C)
10. End the process and feature are classified
11. Data are classified.

V. EXPERIMENTAL RESULT ANALYSIS

In this implement we used MATLAB simulation tool for the evaluation of the performance of proposed algorithm. MATLAB well knows computational software. And the validation of algorithm used three dataset one is iris dataset, Cleveland dataset and cancer dataset [15]. To evaluate the performance of each method, hamming loss (Loss) which are defined as follows [16].

$$Hloss = \frac{\sum_{i=1}^{p}(FPi + FNi)}{p \times n} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

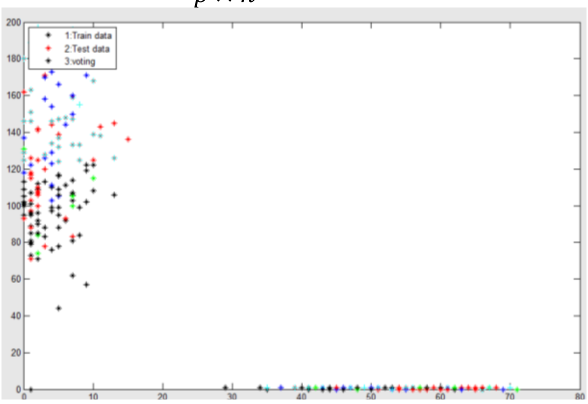

Figure2. Output of on liver dataset with KNNMR method

In the above figure Shows that the output of the Label dependency and Feature Similarity for Multi Label Classification using KNNMR method for of liver dataset and input value of k. k estimate the value of number of participant feature.

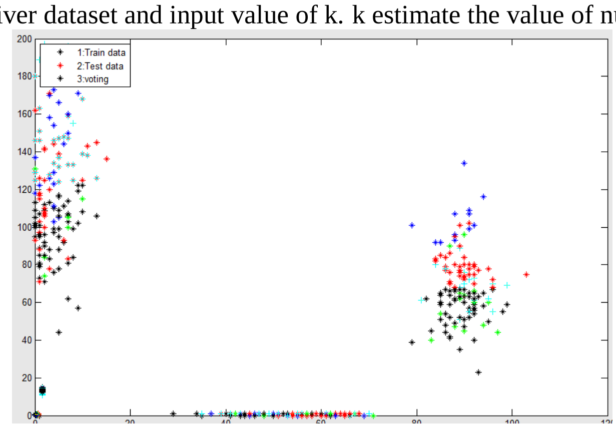

Figure3. Output of on diabetes dataset with IKNNMR method

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In the above figure **S**how that the output of the Label dependency and Feature Similarity for Multi Label Classification using IKNNMR method for of diabetes dataset and input value of k. value of k managed by the TLBO optimization and proceed for the classification.

VI. COMPARATIVE RESULT ANALYSIS

With the help of our implementation work, we have to get several parameters are elapsed time, regression and map with result value.

In the below table Shows the Elapsed, Regression and Map using KNNMR and IKNNMR method for Cleveland dataset and input value is 8 in the Label dependency and Feature Similarity for Multi Label Classification.

TABLE1. Elapsed, Regression and Map on Cleveland dataset using KNNMR and IKNNMR Method

Method	**Elapsed Time**	**Regression**	**Map**
KNNMR	7.048298	0.333333	0.582500
IKNNMR	6.376692	0.285714	0.460000

In the below table Shows the Elapsed, Regression and Map using KNNMR and IKNNMR method for diabetes dataset and input value is 15 in the Label dependency and Feature Similarity for Multi Label Classification.

TABLE2. Elapsed, Regression and Map on diabetes dataset using KNNMR and IKNNMR Method

Method	**Elapsed Time**	**Regression**	**Map**
KNNMR	15.987626	0.416667	1.465500
IKNNMR	15.830380	0.357143	0.958800

In the below table Shows the Elapsed, Regression and Map using KNNMR and IKNNMR method for Ecoil dataset and input value is 18 in the Label dependency and Feature Similarity for Multi Label Classification.

TABLE3. Elapsed, Regression and Map on Ecoil dataset using KNNMR and IKNNMR Method

Method	**Elapsed Time**	**Regression**	**Map**
KNNMR	7.858360	0.166667	0.624500
IKNNMR	7.764233	0.142857	0.586400

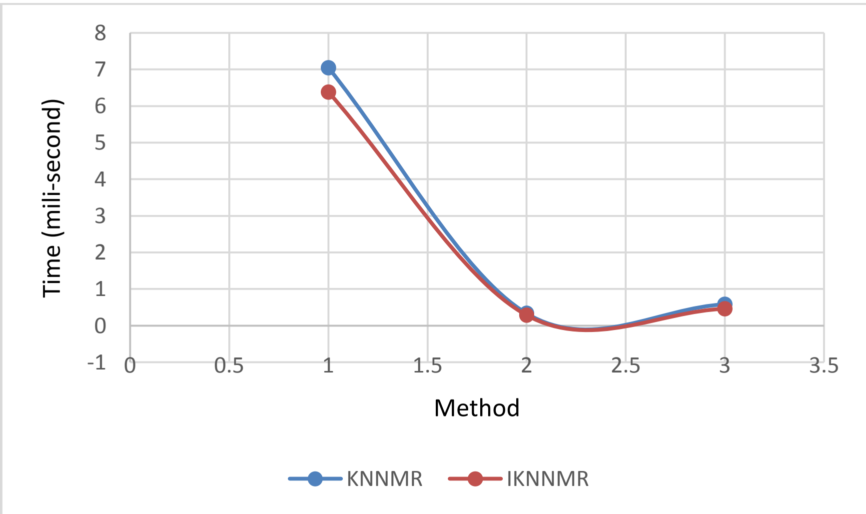

Figure4 Comparative result analysis using KNNMR and IKNNMR for Elapsed Time using Clevelend dataset

In above graph Shows the result analysis on the basis of comparative result analysis study of using Cleveland dataset and input value of k is 8 with Elapsed Time, Regression and Map output values, applied KNNMR method and IKNNMR method in the Label dependency and Feature Similarity for Multi Label Classification.

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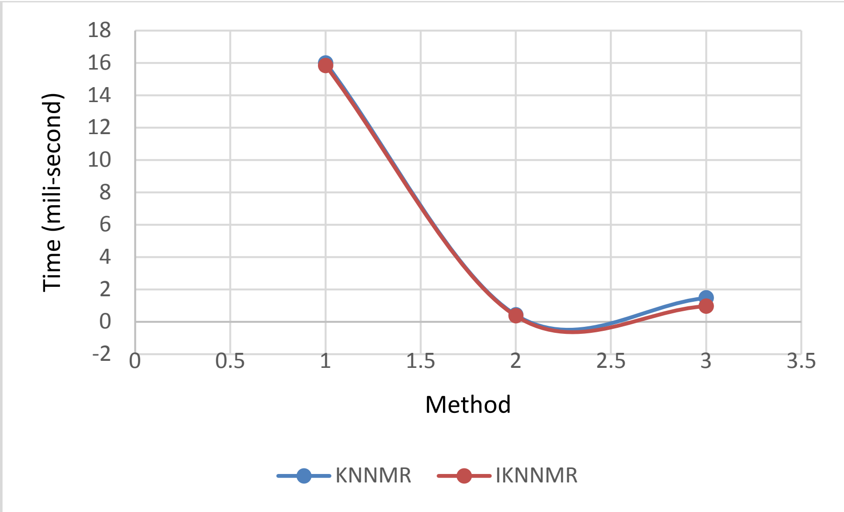

Figure5. Comparative result analysis using KNNMR and IKNNMR for Elapsed Time using Diabetes dataset

In above graph Show the result analysis on the basis of comparative result analysis study of using diabetes dataset and input value of k is 15with Elapsed Time, Regression and Map output values, applied KNNMR method and IKNNMR method in the Label dependency and Feature Similarity for Multi Label Classification.

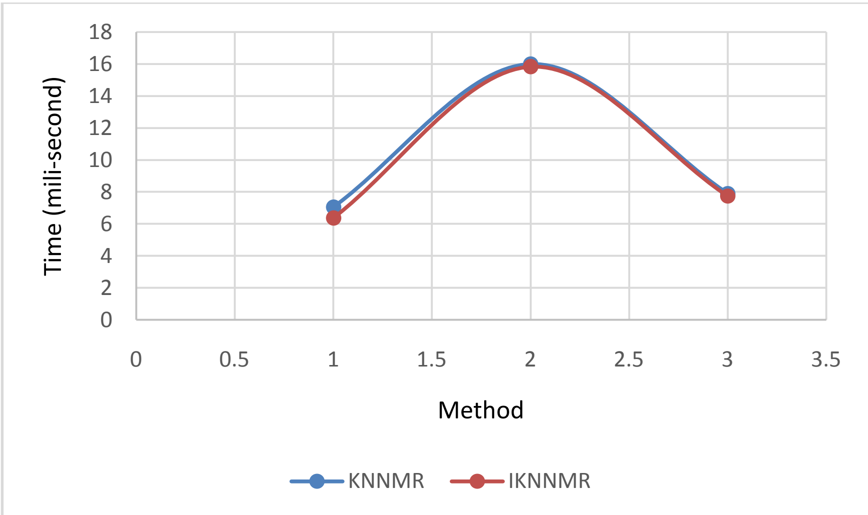

Figure6. Comparative result analysis using KNNMR and IKNNMR for Elapsed Time using Ecoil dataset

In above graph Show the Elapsed Time result analysis on the basis of comparative result analysis study of using Cleveland, Diabetes, liver, iris, glass and ecoil dataset with input value of k, applied KNNMR method and IKNNMR method in the Label dependency and Feature Similarity for Multi Label Classification.

VII. CONCLUSION

In this paper we have proposed improvement based multi-label information arrangement. The procedure of highlight advancement is finished by subterranean insect province improvement. The subterranean insect settlement streamlining gathered the applicable basic component of report to class. For the procedure of characterization utilized group mapping arrangement strategy. The component improvement prepare lessens the loss of information amid the change of highlight mapping amid the characterization. In this paper proposed multi-label classification calculation in light of TLBO algorithm and group mapping strategy. In proposed calculation, the ants' settlement streamlining calculations play an errand of highlight enhancement of information mapping of order. The advancement procedure likewise lessens the issue of information measurements and loss of information. The better choice of highlight gives better consequence of characterization and expectation of information arrangement.

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