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Non-Linear Machine Learning Techniques for Multi-Label Image Data Classification

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Abstract: In this paper, we propose non-linear Machine Learning Techniques (MLT) for Multi-label Image Classification (MLIC) problems. Multi-label Learning requires MLT to identify the complex non-linear relationship between the features and class labels. Also, Multi-label data degrades the performance of the classifiers and processing of this data with a large number of features is too complex while using traditional methods. Therefore, we propose two approaches namely ensemble Deep Learning Network (DLN) and Multivariate Adaptive Regression Splines (MARS) for MLIC. The experimental results show that the proposed (DLN and MARS) algorithms achieves a superior predictive performance rate of 94.77% and 81.68% respectively, compared to the existing methods.

Keywords: Multi-Label (ML), Image Classification, Deep Learning Network, MARS.

1 Introduction

Multi-Label (ML) image learning is an increasingly required concept for the recent real-world applications. Multi-Label Image Classification (MLIC) is a process of assigning multiple labels for each image in the image dataset. An example of MLIC is a picture that can be assigned with multiple labels, namely sky, landscape and forest [1–3]. Image Classification (IC) is a process of labeling the images with many predefined class labels. An image normally contains rich semantic information, namely parts, scenes, objects, actions, and their interactions or features. Different methods have been proposed for image dataset and classification of an image is very difficult to handle because patterns extracted from the same images contain different interpretations based on the position and context [4, 5].

Studies show that a variety of approaches have been proposed such as Deep Convolutional Neural Networks (CNN), a hybrid CNN is proposed for large scale ML image data classification such as Hypothesis CNN-Pooling, CNN-RNN and HCP-CNN [6, 7], Support Vector Machine (SVM) by considering the example label pairs [8, 9] label probabilistic enhancement by considering the co-occurrence patterns of the labels and constructing the tree graph in the label space [10], Structured max margin with co-occurrence matrix-based framework using the feature label and inter-label correlation [11] and transductive matrix and weakly-supervised learning formulated for the low-rank problem [12].

It is understood that Deep Learning Network (DLN) for syndrome diagnosis is proposed with a single hidden layer. In this, 13 node number value for the hidden layer is used to choose the best node value. In general, there is a complex and nonlinear association between features and the multiple class labels. Also, the presence of large numbers of features is the prime issue to address in the Multi-Label Classification (MLC) [13]. Restricted Boltzmann Machine (RBM) model is used to solve the multi-label learning with incomplete labels. Predefined Critical Hyper-Parameters (CHP) are used with single hidden layer and less number of cross-validation. One of the challenging tasks in the DLN is to define the CHP [14]. Classification of MLD using DLN is proposed with the set of hyper-parameters. Several parameters are fine-tuned to select the best set of parameter from the fixed set of a parameter using three-fold cross

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validation [15]. Multi-label classification is proposed in the optical remote sensing application using DLN with sparse auto encoders and a single hidden layer [16]. Therefore, there is a need for an efficient method to define the CHP that can improve the efficiency of the DLN.

Accuracy and reliability of the classification model are important in the decision making. Also, modeling the rich semantic information and their relationship is most important for image mining [17]. Classifier built from the Multi-Label Data (MLD) is more time-consuming with multiple feature subsets. However, various challenges are there in the existing approaches like a large number of labels, imbalance, the correlation among labels and handling missing labels [18, 19]. Therefore, mining of MLD is a very challenging task in existing methods and needs a systematic approach. Pruning, feature selection, handling missing value, handling the continuous attribute, hierarchical structure to manage label correlation and extraction of the relevant label set from multiple labels set are various research challenges in the MLL. In MLC, labels can have strong interdependencies, and some of them may even be missing. Existing multi-label algorithms are unable to handle both issues simultaneously [20]. In general, there is a complex interaction between different features and the class labels [21]. Therefore, there is a need of data mining techniques which supports non-linearity.

Various research issues in the MLC are proposed. They are exploiting the class label association to increase the performance, selection of efficient MLC algorithm which deals with complex and high dimensional data with reduced computational complexity; systematic study that would be helpful to the MLL researcher on how and why the performance varies over different data properties and also to choose MLC algorithms for any particular domain; and design of efficient online MLC that scale with the large and sparse domains is also needed. Traditional classification deals with assigning each instance to a single label. Also, the labels have a hierarchical structure, and its instances can have their class relationship with two or more ways. Most of the existing MLC algorithms do not support hierarchical structure. Providing the comprehensive solution to the hierarchical structure in MLL is an important research dimension [22].

Although existing methods achieved success in some applications, non-linear machine learning techniques has not been explored for the MLIC. To address this challenge, this paper proposes two machine learning techniques which support non-linearity for the MLIC.

2 Multi-Label Image Data Classification Using Deep Learning Network

In this section, a brief overview of the proposed ensemble DLN for supervised learning tasks is provided. The basic information processing unit in the neural network model

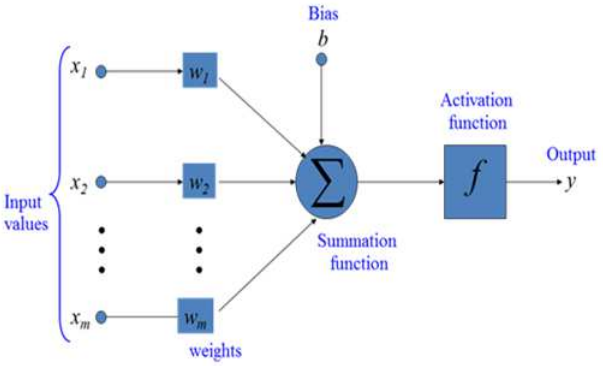

Fig. 1: Basic neural network model

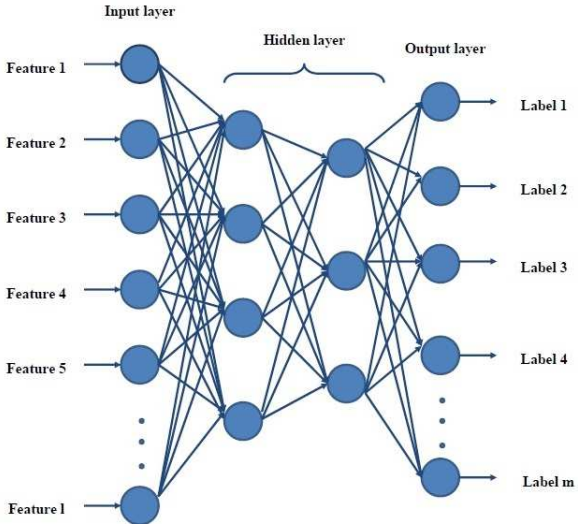

Fig. 2: Proposed structure of DLN for MLD

is shown in Fig. 1. It consists of a set of inputs $(x_1, x_2, x_3, \ldots, x_m)$ with associated weights $(w_1, w_2, \ldots, w_m)$. Weights are randomly chosen initially; typical values are between -1.0 and 1.0 or -0.5 and 0.5.

A summation functions for calculating the weighted sum of the inputs

$$\alpha = \sum_{j=1}^{m} w_j x_j \tag{1}$$

The choice of the nonlinear activation function f determines the neuron model and bias b, neuron's activation threshold

$$y = f(\alpha + b) \tag{2}$$

In the literature, various deep learning frameworks are available and in this research work feed-forward neural network architecture is used. The proposed multi-layer feed forward structure of DLN for MLD is illustrated in Fig. 2. It is a multilayer network, which includes input (feature space), output (linear regression or classification) with many hidden layers of non-linearity. The input and output of the proposed model use the same procedure

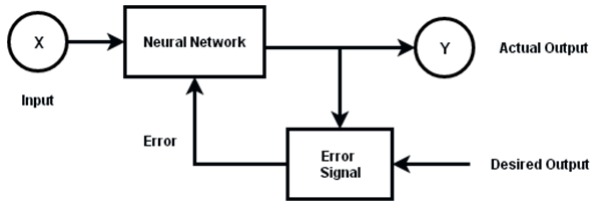

Fig. 3: Supervised learning training process for DLN

which is followed in the single neuron model as described above. The weight and bias function is used to determine the output of the entire network [23]. In this DLN, the objective function is to minimize the loss function for each training instances j, which is given by $L(W,B \mid j)$, W is the collection $\{W_i\}_{1:N-1}$, where W_i the weight matrix layers i and $i+1$ for a network of N layers. Similarly, B is the collection $\{b_i\}_{1:N-1}$, where b_i denotes the column vector of biases for layer $i+1$.

DLN training is divided into two phases; pre-training and discriminating fine tuning. Initially learning network uses the greedy learning algorithm in layer-wise and using Restricted Boltzmann Machine (RBM) which trains the network layer by layer. To optimize the parameters, it uses the supervised learning algorithm. That is a combination of unsupervised pre-training followed by the supervised training. In this research work, it is purely supervised training process that has been used, until the desired output is reached with the minimized error the learning parameters are adjusted. Supervised learning and training process is shown in Fig. 3.

The steps of the supervised learning process are given below:

1.Each input vector contains a corresponding target vector, which is called as the desired output. Each training pair contains an input vector and target vector.
2.Based on the input vector at each iteration, NN results the output vector.
3.The resulted output vector is compared with the original output vector
4.The error signal is generated if there is a deviation between the desired output and actual output.
5.The error is used to adjust the learning parameter to improve the performance of the NN.
6.The same process continues until the desired output reaches with the minimal error.

3 Multi-Label Image Data Classification Using MARS

MARS is a regression-based technique. Its outputs are a linear function that is readily understood by the analyst and can be used to explain the model for management [24]. It deals with multidimensional data, evaluating each factor and possible interaction among them. It eliminates a certain number of predictors if they

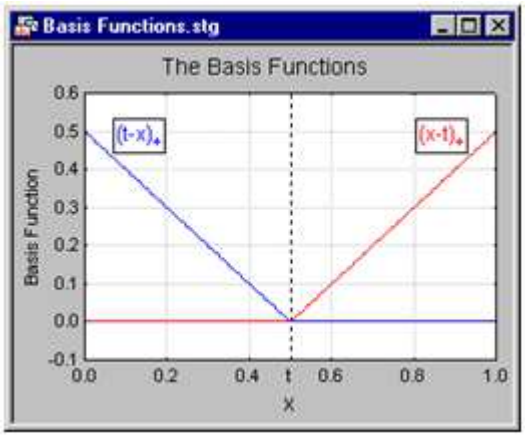

Fig. 4: Simple piecewise linear regression

do not contribute to increasing the performance of the final model [24].

MARS model of the form

$$\hat{f}(x) = \sum_{i=1}^{k} c_i B_i(x) \tag{3}$$

The model is a weighted sum of basis functions $B_i(x)$. Each c_i is a constant coefficient. Each basis function $B_i(x)$ takes one of the following three forms:

–a constant 1. There is just one such term, the intercept.
–a hinge function has the form $\max(0, x-c)$ or $\max(0, c-x)$, where c is a constant called the knot.
–a product of two or more hinge functions.

MARS uses the basis function to establish the relationship between the independent and dependent variables, which creates multiple peace wise linear regression using the breakpoint. The simple piecewise linear regression with two basis function $(t-x)+$ and $(x-t)+$ is shown in Fig. 4, where c is the knot, which defines the breakpoint for the piecewise linear regression, "+" signs define that it considers only the positive results of the respective basis function; otherwise it uses zero to evaluate.

3.1 Most Important Predictor Identification

The most significant predictor is always increasing the predictive accuracy of the classifier model. Furthermore, large numbers of features are the prime issue to address in Multi-Label Learning (MLL). It is computationally high and very complex for further analysis or to build a classifier. Generalized Cross Validation (GCV) is used to identify the most significant predictor. Friedman uses the modified form of the GCV that is used to identify the most significant predictor, rank the predictor and eliminate insignificant predictor of the model [24].

If a variable receives a score of 100, it is the most significant predictor, and the variable receives a score 0

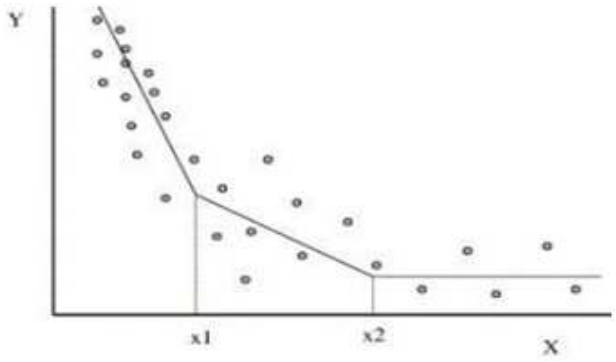

Fig. 5: Simple MARS model with Knots

which is not used in the MARS model. GCV is defined as

$$GCV(M) = \frac{\frac{1}{N}\sum_{i=1}^{N}\left[y_i - \hat{f}_M(x)\right]^2}{\left[1 - \frac{C(M)^*}{N}\right]^2} \quad (4)$$

where

$$C(M)^* = C(M) + \delta M \quad (5)$$

–N is the number of observations
–$C(M)^*$ is a complexity cost function of the model generating f, the default is to set equal to a function of the effective number of parameters
–M is the number of non-constant basis functions in the MARS model and
–δ is a cost for each basis-function optimization and is a smoothing parameter for the procedure.

MARS model is the two-step process, in the initial step it builds the model by adding the basis function in Eq. (3) until it reaches the user-defined number. Then in the second step, it applies the backward procedure to remove the redundant basis function from the Eq. (3) until the final model result with the minimum GCV (4) is obtained. It finds the most significant independent variable and interaction among them. MARS is used for multiple dependent variables in which it determines a set of basis function but estimates different coefficients for each dependent variable. Compared with the neural network, MARS treats multiple dependent variables. The simple model of MARS with the dependent (Y) and independent (X) variables with piecewise linear regression splines using the knot x_1 and x_2 is shown in Fig. 5. From Fig. 5, it is easy to understand that the MARS model is building the non-linear relationship between the input and output variables by integrating all the linear relationship.

4 Experimental Setup and Evaluation Criteria

Evaluation is one of the important phases of the data mining process. It helps to identify the best model that represents our training data and shows how well the final model works on the prediction. Estimating the performance of the model with the data used for training generates a non-realistic and over-optimistic prediction. This section illustrates the experimental setup and evaluation criteria of the proposed DLN and MARS algorithm. Proposed DLN and MARS do not deal with the MLL directly; therefore, the MLD is transformed into Single Label Dataset (SLD) using any one of the problem transformation methods namely Binary Relevance (BR) and Label power set (LP).

To evaluate the proposed ensemble DLN and MARS methods for the scene data classification in the MLL, experiments have been carried with the ML scene dataset. The details of the dataset are depicted in Table 1. The proposed ensemble DLN framework is implemented in R-language with H2O in the Hadoop/Map Reduce. H2O is a fast, scalable online machine learning platform, which models, data very fast and easy to make better decisions faster by running advanced data mining algorithms.

To evaluate the effectiveness of the proposed ensemble DLN and MARS algorithm, multiple evaluation measures are computed including F1 statistic, accuracy, precision, sensitivity and specificity. The sensitivity of the MARS and DLN model based on the several parameters like (Basis function, Knots, Interaction for MARS) and (Activation function, Hidden Layer, Epochs, Rho and epsilon etc., for DLN) is to improve the classifier accuracy. Experimental results of MARS with different parameter setting are depicted in Table 2. In Table 3, the best results of the MARS algorithm are depicted based on different parameter settings (Basis Function, Interaction and Knots). In Table 3, the results of DLN algorithm are depicted, and the proposed DLN model results in a test set error of 0.9% or better. We use activation function = rectifier with dropout, hidden layer $= C(250,250,500)$, epochs $= 1000$, $L_1 = 10^{-5}$, input dropout ratio $= 0.2$, $\rho = 0.99$, $\varepsilon = 10^{-8}$ and $\max w_2 = 15$ for the proposed DLN model.

Table 1: Details of the used dataset

Data set	No. of Instances	No. of Features	No. of Target
Scene	2407	294	6

5 Experimental Results and Discussions

In Table 3, the accuracy of the proposed MARS and ensemble DLN are compared. From Table 3, it is observed that the ensemble DLN is the best classifier compared with the proposed MARS for the scene data classification for all the six class labels. Also, in Table 4, the accuracy of the proposed MARS and ensemble DLN and previously proposed methods in the literature are compared.

From Table 4, it is evident that the 74.2% as the highest accuracy using DBN2ECC for the classification of scene dataset. As shown in Table 4, ensemble DLN and

Table 2: Experimental results of MARS with different parameter settings

S.No.	Label	MBF	MI	Average	Overall average	Specificity	Sensitivity	Precision	F1 Statistic
1	Beach	15	(5,10,15)	83.97	82.84	82.22	85.71	50.97	63.93
		20	(5,10,15)	84.82	83.34	82.53	87.12	51.81	64.98
		25	(5,10,15)	85.79	82.97	81.41	90.16	51.13	65.25
2	Sunset	15	(5,10,15)	91.13	88.78	87.76	94.51	57.91	71.82
		20	(5,10,15)	91.46	89.53	88.69	94.25	59.76	73.13
		25	(5,10,15)	92.17	89.78	88.74	95.60	60.21	73.81
3	Fallfoliage	15	(5,10,15)	88.05	84.25	82.39	93.70	51.24	66.25
		20	(5,10,15)	88.82	85.38	83.68	93.95	53.21	67.94
		25	(5,10,15)	89.78	85.13	82.84	96.73	52.67	68.21
4	Field	15	(5,10,15)	90.08	87.58	86.17	94.00	59.85	73.14
		20	(5,10,15)	90.83	88.37	86.98	94.69	61.47	74.55
		25	(5,10,15)	91.67	89.45	88.20	95.15	63.88	76.44
5	Mountain	15	(5,10,15)	76.01	70.38	5.90	86.12	41.80	56.23
		20	(5,10,15)	76.46	71.50	67.56	85.37	42.80	57.02
		25	(5,10,15)	78.20	73.58	69.90	86.49	44.98	59.18
6	Urban	15	(5,10,15)	79.74	72.25	68.07	91.42	38.44	54.12
		20	(5,10,15)	80.38	72.25	67.71	93.04	38.59	54.56
		25	(5,10,15)	80.97	73.37	69.13	92.81	39.60	55.52

Table 3: Comparison of DLN and MARS

S.No	Label	Average		Overall Average	
		DLN	MARS	DLN	MARS
1	Beach	0.9016	84.86	0.9043	83.05
2	Sunset	0.9597	91.58	0.9663	89.36
3	FallFoliage	0.9550	88.88	0.9589	84.82
4	Field	0.9156	90.71	0.9295	88.46
5	Mountain	0.8702	76.89	0.8720	71.82
6	Urban	0.9049	80.36	0.9106	72.62

Table 4: Comparing Multi-Label Methods under Accuracy. Proposed with Existing methods

Algorithm	DBN3bp	DBN2ECC	MLkNN	IBLR	ECCR	ECC	RAk	FW	BPMLL	MARS	DLN
Accuracy	0.731	0.742	0.696	0.697	0.731	0.710	0.684	0.649	0.552	0.8168	0.9477

MARS algorithm achieves the better accuracy rate 94.77% and 81.68% respectively, compared with the existing methods in the literature with less number of features. Also, the proposed framework ensemble DLN yields significant performance improvement when compared with existing methods in the literature. DLN and MARS have various advantages when compared with the existing methods in the literature. It deals with the complicated and large dataset, extract a relevant subset of features from a large number of features to reduce the computational complexity. In particular, it supports to identify the complex nonlinear relationship between the features and class labels. Also, it supports to handle missing values, imbalanced data. DLN learns a useful representation of raw data and considers the hierarchical structure of the labels. In conclusion, it indicates that the MLL based on MARS and ensemble DLN method is superior to other MLL methods in the literature for the scene data classification.

6 Conclusion

The paper presents two machine learning techniques namely ensemble DLN and MARS which support non-linearity for MLIC problems. From the experimental results, it is evident that the proposed MARS and DLN algorithms perform well when compared to the existing methods in terms of speed and accuracy. Also, an improvement of up to 15 percentage in accuracy with less number of features compared with the original feature space. Furthermore, the proposed methods outperform the existing methods in terms of various features mentioned in the paper. In conclusion, the study serves as a reference for designing the framework for those exploring further avenues in the MLIC and also those applications generating MLD.

References

[1] Z. Abdallah, M. Oueidat and A El-Zaart, An Improvement of Multi-Label Image Classification Method Based on Histogram of Oriented Gradient, World Academy of Science, Engineering and Technology, International Journal of Computer, Electrical, Automation, Control and Information Engineering, Vol. 11, No. 2, pp. 196–199 (2017).

[2] J. Wang,Y. Yang, J. Mao, Z. Huang, C. Huang, and W. Xu, CNN-RNN: A Unified Framework for Multi-Label Image Classification, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 2285–2294 (2016).

[3] Z. Li, W. Lu, Z. Sun and W. Xing, Improving Multi-Label Classification Using Scene Cues, Multimedia Tools and Applications, Vol. 77, No. 5, pp. 6079–6094 (2018).

[4] Agnelli, Davide, Alessandro Bollini, & Luca Lombardi, Image Classification: An Evolutionary Approach, Pattern Recognition Letters, Vol. 23, No. 1–3, pp. 303–309 (2002).

[5] Zahradnikova, Barbora, SonaDuchovicova, and Peter Schreiber, Image Mining: Review and New Challenges, International Journal of Advanced Computer Science and Applications, Vol. 6, No. 7, pp. 242–246 (2015).

[6] Y. Wei, W. Xia, M. Lin, J. Huang, B. Ni, J. Dong, and S. Yan, HCP: A Flexible CNN Framework for Multi-Label Image Classification, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 38, No. 9, pp. 1901–1907 (2016).

[7] J. Wang, Y. Yang, J. Mao, Z. Huang, C. Huang, and W. Xu, CNN-RNN: A Unified Framework for Multi-Label Image Classification, Proceedings of the twenty ninth IEEE International Conference on Computer Vision and Pattern Recognition, pp. 2285–2294 (2016).

[8] X. Li, L. Wang and E. Sung, Multilabel SVM Active Learning for Image Classification, Proceedings of IEE International Conference on Image Processing, Vol. 4, pp. 2207–2210 (2004).

[9] Aiwen Jiang, Chunheng Wang, Yuanping Zhu, Calibrated Rank-SVM for Multi-Label Image Categorization, Proceedings of IEEE International Joint Conference on Neural Networks, pp. 1450–1456, (2008).

[10] X. Li, F. Zhao and Y. Guo, Multi-label Image Classification with a Probabilistic Label Enhancement Model, Proceedings of the thirtieth Conference on Uncertainty in Artificial Intelligence UAI'14, pp. 430–439 (2014).

[11] X. Xue, W. Zhang, J. Zhang, B. Wu, J. Fan, and Y. Lu, Correlative Multi-Label Multi-Instance Image Annotation, Proceedings of International Conference on Computer Vision, Barcelona, pp. 651–658 (2011).

[12] R. Cabral, F. De la Torre, J. P. Costeira, and A. Bernardino, Matrix Completion for Weakly-Supervised Multi-Label Image Classification, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 37, No. 1, pp. 121–135 (2015).

[13] G.P. Liu, J.J. Yan, Y.Q. Wang, W. Zheng, T. Zhong, X. Lu and P. Qian, Deep Learning Based Syndrome Diagnosis of Chronic Gastritis, Computational and Mathematical Methods in Medicine, Vol. 2014, No. 3. pp. 1-8 (2014).

[14] X. Li, F. Zhao, and Y. Guo, Conditional Restricted Boltzmann Machines for Multi-Label Learning with Incomplete Labels, Proceedings of the eighteenth International Conference on Artificial Intelligence and Statistics, San Diego, Vol. 18, pp. 635–643 (2015).

[15] J. Read, and F. Perez-Cruz, Deep Learning for Multi-Label Classification, arXiv preprint arXiv:1502.05988 (2014).

[16] K. Karalas, G, Tsagkatakis, M, Zervakis and P. Tsakalides, Deep Learning for Multi-Label Land Cover Classification, Image and Signal Processing for Remote Sensing XXI, Proceedings of SPIE, Vol. 9643, pp. 1–14 (2015).

[17] Guo, Hongyu, and Sylvain Lé tourneau, Iterative Classification for Multiple Target Attributes, Journal of Intelligent Information Systems, Vol. 40. No. 2, pp. 283–305 (2013).

[18] Yu, Hsiang-Fu, Prateek Jain, PurushottamKar, and Inderjit Dhillon, Large- Scale Multi-Label Learning with Missing Labels, Proceedings of the thirty first International Conference on Machine Learning, pp. 593–601 (2014).

[19] L.M. Romão and J.C. Nievola, Hierarchical Multi-Label Classification Problems: An LCS Approach, Distributed Computing and Artificial Intelligence, Proceedings of the twelve th International Conference Advances in Intelligent Systems and Computing, Vol. 373, Cham, pp. 97–104 (2015).

[20] Prajapati, Purvi, AmitThakkar, and AmitGanatra, A Survey and Current Research Challenges in Multi-Label Classification Methods, International Journal of Soft Computing and Engineering (IJSCE), Vol. 2. No. 1, pp. 248–252 (2012).

[21] H. Wang, X. Liu, B. Lv, F. Yang, and Y. Hong, Reliable Multi-Label Learning Via Conformal Predictor and Random Forest for Syndrome Differentiation of Chronic Fatigue in Traditional Chinese Medicine, PloS One, Vol. 9, No. 6, e99565 (2014).

[22] S. Sorower, Mohammad, A Literature Survey on Algorithms for Multi-Label Learning, Oregon State University, Corvallis 18, 1–25, 2010.

[23] A. Candel,V. Parmar, E. LeDell, and A. Arora, Deep Learning with H2O, Fourth Edition, pp. 1–52 (2015).

[24] L. Francis and Martian, Chronicles: Is MARS Better than Neural Networks, In Casualty Actuarial Society Forum, pp. 1–37, 2003.

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