A Novel Approach to Improve the Performance of HMI Model Using Bilateral Data Prediction with Neural Network Data Mining From Social Network Using Neural Network

JAYAPAL P

Dept. of Electrical and Electronics Engineering, North East Frontier Technical University(NEFTU), Medog, Aalo, Arunachal Pradesh, India

Abstract- In this, the data pattern from the sensor can be extracted by using the Equalized Distribution Pattern (EDP) model to find the relevancy between the feature of query data and from the entire dataset and form as the cluster of combination. To enhance the HMI model, the virtual management process are takes care based on the prediction of sensor parameters and to identify the range of parameters with supervised data learning. This type of data learning can be achieved by the improved bilateral neural network technique. To find the matching feature, the Bilateral Data Prediction with Neural Network (BDP-NN). With this system, first the pre-processed feature is matched with the pattern by using BDP-NN to find the type of data without directly passed into the whole dataset. From that type identified result, the similarity between the matched result and overall dataset is retrieved by using the EDP method to display all matched result from the bulk dataset with better classification result.

Indexed Terms- Clustering, Database management, Data prediction, Feature extraction, Neural network

I. INTRODUCTION

Data Mining (DM) defined as extracting already existing useful information and processing of those extracted or mined valuable information from high volume warehouse. The primary process of DM is observing the data to use in various directions and determining the useful information in the most summarised format to get informative knowledge. Pattern classification using hybrid intelligent systems is an active research and application area. [1] A problem of classification arises when the user needs to assign the objects or patterns into a predefined cluster or class based on a number of observed features of those patterns. The design of a pattern classification and recognition systems require careful attention of “definition of pattern classes, sensing environment, pattern representation, feature extraction and selection, cluster analysis, classifier design and learning, selection of training and test samples and performance evaluation” [2].

The research over the past few decades in the field of pattern classification and recognition has shown that, of all the available technologies have its own strengths or weakness. Therefore, many times it is beneficial to use number of pattern classification techniques collectively rather than exclusively. This results in the construction of complementary hybrid intelligent systems. Thus, at present, hybrid systems which combine the strengths of the components of Computational Intelligence (CI), that include Neural Network (NN), Fuzzy Logic (FL) and/or Genetic Algorithm (GA), are popular for pattern recognition and classification [3], [4].

- *Prediction:*

Prediction has drawn considerable attention given the probable effects of successful prediction in a business context. There are two key types of predictions: one can try to either predict some pending trends or unavailable data values, or predict a class label for some data. The latter linked to classification. Once a classification model is built centered on a training set, the class label of an object can be forecasted based on the feature values of the objects and classes. Prediction is nevertheless, more often related to the estimation of missing numerical values, or decrease/increase trends in time-associated data. The main idea is to utilize large numbers of past values to take into account possible future values. [5]

- *Clustering:*

Clustering is the organisation of data in classes. In clustering, class labels are unknown and it is up to the clustering algorithm to ascertain acceptable classes. Clustering is also known as unsupervised classification, since the classification is not determined by the given class labels. There are several clustering approaches, all centered on the principle of maximising the similarity between objects in a same class (intra-class similarity) and minimising the similarity between objects of different classes (inter-class similarity). [6]

- *Neural Network Architectures:*

The ANN are made of many processing elements called as neurons. The arrangement of the connections in between these neurons within and in-between layers is generally called as the architecture of the neural network. The neurons within a layer may be fully interconnected or not interconnected. [7] In general, all the neural network architectures are of two types as below.

1. Feed-Forward networks
2. Recurrent networks

In this proposed work we are using hierarchical type of clustering. We test our approach against a well-known data set containing a range of classes, instances, and attributes in order to determine how effective the suggested algorithm is.

Objectives of this paper are as follows:

- To develop an enhanced model of data prediction for improving the performance of virtual HMI system.
- To match the sensor data with an optimal pattern and clustering using the EDP method.
- To enhance the data prediction system by the BDP combined with the Neural Network.
- To analyse the performance of prediction and the overall HMI model compared with traditional model of data prediction techniques.

The paper is alienated into six main segments. Section I deals with introduction to research work with elementary explanation of concepts. Section II is about the related work and to evaluate the review for new proposed work. The section III deals with the explanation of proposed work mainly with the proposed methodology and algorithm. The section IV and V described about the experimentation and results. Last section VI contains conclusion of paper and future suggestions of the proposed work.

II. RELATED WORK

Fuzzy neural networks are one of the effective techniques used in the domain of pattern classification. However, till date, NN has been applied only on small datasets with the impediment of providing ample features for producing quality results. In actuality, any attempt to label extensive datasets to train NN for pattern classification and recognition purpose will be futile.

- In [8] is one of the most remarkable methods in this field, which combines autoencoder with the k-means algorithm. In the first step, its pre-trains an autoencoder. Then, it jointly optimizes the reconstruction loss and k-means loss. Since k-means uses discrete cluster assignments, the method requires an alternative optimization algorithm. The objective of DCN is simple compared with other methods and the computational complexity is relatively low.
- In [9] proposes a deep embedding network to extract effective representations for clustering. It first utilizes a deep autoencoder to learn reduced representation from the raw data. Secondly, in order to preserve the local structure property of the original data, a locality preserving constraint is applied. Furthermore, it also incorporates a group sparsity constraint to diagonalize the affinity of representations. Together with the reconstruction loss, the three losses are jointly optimized to fine-tune the network for a clustering-oriented representation. The locality-preserving and group sparsity constraints serve as the auxiliary clustering loss, thus, as the last step, k-means is required to cluster the learned representations.

- In [10] introduces a novel autoencoder architecture to learn an explicit non-linear mapping that is friendly to subspace clustering [11]. The key contribution is introducing a novel self-expressive layer, which is a fully connected layer without bias and nonlinear activation and inserted to the junction between the encoder and the decoder. This layer aims at encoding the self-expressiveness property [12] [13] of data drawn from a union of subspaces.
- In [14] is an efficient and reliable deep clustering algorithm which can deal with large-scale image datasets. It proposes a CNN-based framework to solve clustering and representation learning iteratively. It first randomly picks k samples and uses an initial model pre-trained on the ImageNet dataset to extract their features as the initial cluster centroids. In each step, minibatch k-means is performed to update assignments of samples and cluster centroids, while stochastic gradient descent is used to update Page | 251the parameters of the proposed CNN.
- Neural networks are the massively parallel structures composed of "neuron" like subunits [15]. Neural networks provide efficient result in the field of classification. Its property of changing its weight iteratively and learning [16], [17], give it an edge over other techniques for recognition process. Perceptron is a primitive neuron model. It is a two-layer structure. If output function of perceptron is step, then it performs classification problems, if it is linear than it performs regression problems. The most commonly used family of neural networks for pattern classification is the feed forward networks like MLP and RBF networks [18]. Different types of neural networks are used depending upon the requirement of the application.

III. PROPOSED WORK

The analysis data learning and grouping represents a dynamic update of data value in a database are main important factor for the Human to machine interaction. In the real time process, the Human to machine communication became a high priority for the industrial and the other applications that are used for monitoring the machine conditions. Researchers mainly focused on the prediction and forecasting of the signal parameters based on the sensor data and other signals that are received from the unit. [19] In general, the application such as like the home automation and the industrial machine running process, the control unit predict the signal range by matching the training pattern overt the time and correlate with the conditions and attributes. This was processed by using the machine learning concept of forecasting system that is considered as the virtual management of instruments and machineries. There are several other methods were developed the Human to Machine Interface system that predicts and forecast the condition of data by updating every time interval. [20]

Even by using the deep learning method of machine earning concept, it requires a greater number of training features to improve the accuracy of predicting the parameter in a sensor data. There are several methods in data learning and analyse the database contents like neural techniques and other machine learning technics. In that, sequence pattern method with the several Neural Network were most commonly used to classify and match the relevant features from database. [21]

To enhance the HMI model, the virtual management process are takes care based on the prediction of sensor parameters and to identify the range of parameters with supervised data learning. This type of data learning can be achieved by the improved bilateral neural network technique. In this, the data pattern from the sensor can be extracted by using the Equalized Distribution Pattern (EDP) model to find the relevancy between the feature of query data and from the entire dataset and form as the cluster of combination. To find the matching feature, the Bilateral Data Prediction with Neural Network (BDP-NN). [22] With this system, first the pre-processed feature is matched with the pattern by using BDP-NN to find the type of data without directly passed into the whole dataset.

A.Proposed Model

Proposed model considers these modules as preprocessing, grid formation, pattern formation, classification and data prediction. Figure 1 presented the stepwise formation of proposed model which mainly includes following steps.

1) Pre-processing: This step includes the selection of data input and process for its testing.
2) Grid formation: this steps incvolves the formation of grids using above part of clustering. The grid specifies the type of sentiment of data as per their opinion values. This steps uses the input coming from the feature selection part which is perfromed using neural networking.
3) Pattern formation: This step perfrom the pattern formation using EDP method. The input data used as the grid formed in above step. The output of this step used as neurons of input of neural network.
4) Classification result: output of features database from the training of dataset and output from neural network prepares the classification results that shows the data for prediction.
5) Data prediction: final output of the whole process are in form of data prediction patterns.

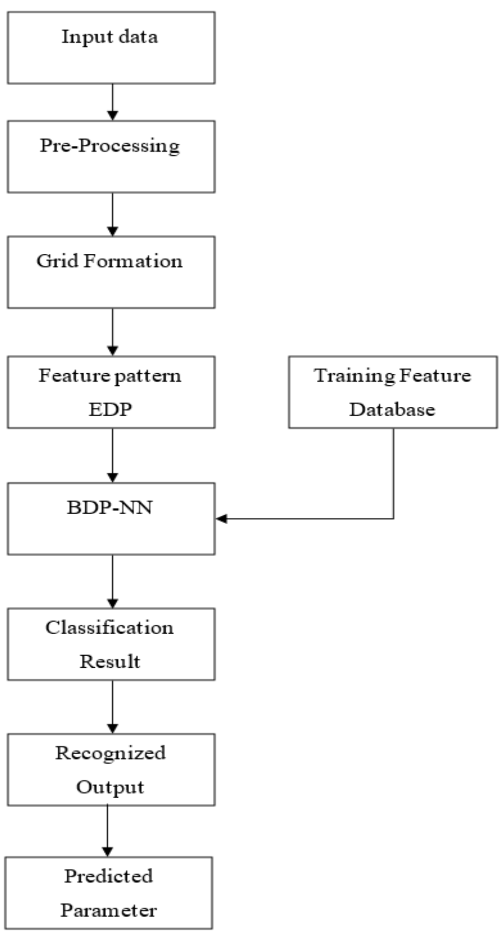

Fig. 1: Block diagram of proposed model

A. Proposed techniques

There are two major techniques used for proposed work. That are as follows:

1. Equalized Distribution Pattern (EDP):

Input: Input Data T_D

Output: Features of attributes $F_D(s)$.

Run For loop for 'M' number of iteration

i = 1 to M (1)

Initialization of attributes like 'y'and the weight value 'α'

$$y(n) = \{y_0, y_1, \ldots, y_m\} \quad \forall\, n = 1, 2, \ldots, m \qquad (2)$$

Where, 'm' represents the number of attributes

$$\omega_i(n) = \left(\frac{q_i^n(y(n))}{\sum_{l=1}^{N}\left(q_i^n(y(n))\right)}\right) \quad \forall\, n = 1, 2, \ldots, m \quad (3)$$

Where, $\omega_i(n)$ represents the weight value of attributes for i^{th} iteration.

where, Potential of the attributes

$$P_t^n = e^{\left\{-\sum_{y \in T_D} f_i(y)\right\}} \qquad (4)$$

Probability estimation of the attributes by

$$L_{1:i}^m = L_{1:i-1}^m \times L_i^m \qquad (5)$$

where, $L_i^m = \frac{1}{N}\sum_{l=1}^{N} P_i^n\big(y(n)\big)$ (6)

Update weight value,

$$\omega_i(n+1) = \sum_{l=1}^{N} \omega_i(n)\, \delta(x_n) \qquad (7)$$

Update Attributes,

$$y(n+1) = \frac{1}{N}\sum_{l=1}^{N} \delta(y_n) \qquad (8)$$

Find max probability value as

$$m_i^* = max(L_{1:i}^m) \qquad (9)$$

Find maximum relevance value,

$$\omega_i^*(n) = max\left(P_i^n\big(y(n)\big)\omega_i(n)\right) \qquad (10)$$

If $(m_i^* > m_{i-1}^*)$, then update weight value of attributes and get best relevance value to form feature set.

If $(L_{1:i}^m) > 0$, then, $s_v = \{s_{v-1}, i\}$ (11)

Continue for loop 'i'.
If $F_D(s) = T_D(s_v)$ (12)

2. Bilateral data prediction with Neural network (BDP-NN) classifier:

Input: Training set, the input series are arranged in the sequential order as, $F_D(s)$

Output: Classified Result $V(k)$

Initialize the feature properties.
$F_D(s) = \{T_{D1}(s), T_{D2}(s), \dots, T_{Dm}(s)\}$ (13)

In the input layer of classifier, the data sequence can be formed as the matrix as in below equation.

$$X_D(s) = \begin{bmatrix} F_{D1}(s) \\ F_{D2}(s) \\ \cdots \\ F_{Dm}(s) \end{bmatrix} \quad (14)$$

Where, above represents the Matrix arrangement for input layer in the Block separation.

Form the matrix arrangement, the block correlation feature can be estimate by $F\left(X_D(s).X_D^*(s)\right)$. This can be representing as

$$F\left(X_D(s).X_D^*(s)\right) = X_D^*.e^{T-T_m} \quad (15)$$

'T' and 'T_m' represents the attribute values from matrix $X_D(s)$.

Estimate the kernel model of classifier

$$K_m = \frac{1}{2^{q-1}}\left(\frac{\sqrt{2q}}{l}\right)^q k_q\left(\frac{\sqrt{2q}}{l}r\right) \quad \forall\, q = 1, 2, \dots, N \quad (16)$$

Where'r' represents range of feature distance, 'l' represents the length of feature vector.

Estimate the relevancy using kernel function with feature points.
Texture relevancy $t_n = F^T\omega_n$ (17)

Where, 'ω_n' weight value of attributes.
$u_n = F^T\omega_n$ (18)

Extract the training features and form the network by
$T_r = \{t_1, t_2, \dots, t_n\}$ (19)

$$X_b = \overline{X_b} + \sum_{i=1}^{N} t_i(d)p^i \quad (20)$$

Estimate the matching score for the correlated blocks by

$$\widehat{T}_s = \left(\left(X_b^{\bar{d}} - \overline{X_b}\right)^T (P^T)\right)^T \quad (21)$$

Where, the relevance factor $X_b^{\bar{d}} \in R^{(T-T_p)M}$ can be written as

$$R^{(T-T_p)M} = \widehat{T}_s{}^T Q^T + \overline{tt_a} \quad (22)$$

Where, 'P' and 'Q^T' are denoted as Predicted component.

The predicted label can be representing by

$$V(k) = \frac{d_{ij}}{R_j - R_i} \quad (23)$$

Where, d_{ij} – Distance matrix for 'i' and 'j' of the relevance matrix 'R'.

IV. RESULT AND ANALYSIS

Comparative result analysis has confirmed the development of proposed work by using the mentioned dataset as shown in below figures.

Table 1: Precision (%) analysis with different training set

Training Model	SimpleNet	AlexNet	GoogleNet	Proposed
CIFAR-100	63.81	72.31	74.62	83.14
STL-10	60.49	83.23	81.92	83.76
CIFAR-10	81.69	90.58	90.59	91.24

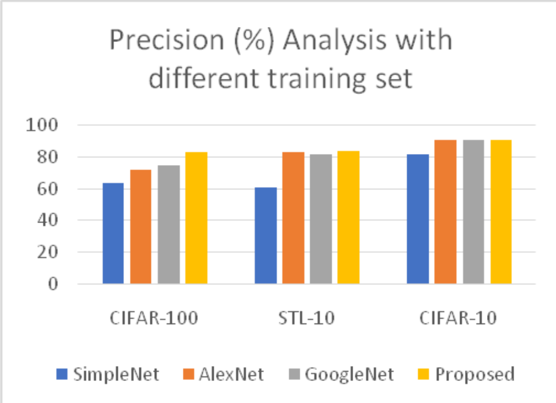

Fig. 2: Precision (%) analysis with different training set

In figure 2 and table 1 results obtained are the comparison among different existing techniques like SimpleNet, AlexNet, GoogleNet vs. proposed techniques for the performance. The performance parameter is precision with different training set like CIFAR-100, STL-10 and CIFAR-10. On the basis of these results showed that for different parameters the performance values of proposed technique are highest as compared to others.

Table 2: Max F1-score analysis with different training set

Training Model	AlexNet	GoogleNet	Proposed
CIFAR-100	71.855	75.016	77.004
STL-10	49.869	62.016	64.189
CIFAR-10	37.425	38.63	40.683

In fig.3 and table 2 results obtained are the comparison among different existing techniques like AlexNet, GoogleNet vs. proposed techniques for the performance. The performance parameter is F1 score with different training set like CIFAR-100, STL-10 and CIFAR-10 On the basis of this graph results showed that for different parameters the performance of proposed technique is highest as compared to others.

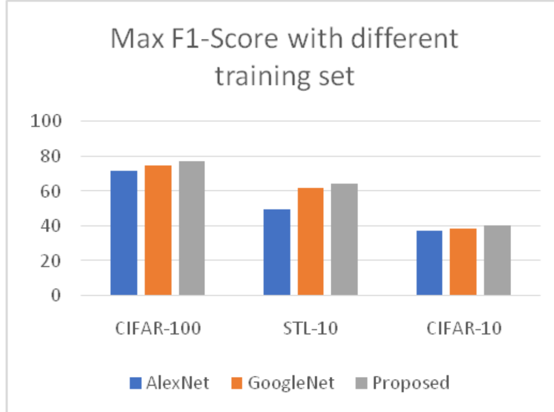

Fig. 3: Max F1-score analysis with different training set

Table 3: Comparative analysis among existing and proposed methods based on different parameters

Parameters	SVM	BCFPM	Proposed
Sensitivity	0.86274	0.90825	0.91743
Specificity	0.95851	0.98226	0.98447
Precision	0.82243	0.92523	0.93457
Recall	0.86274	0.90825	0.91743

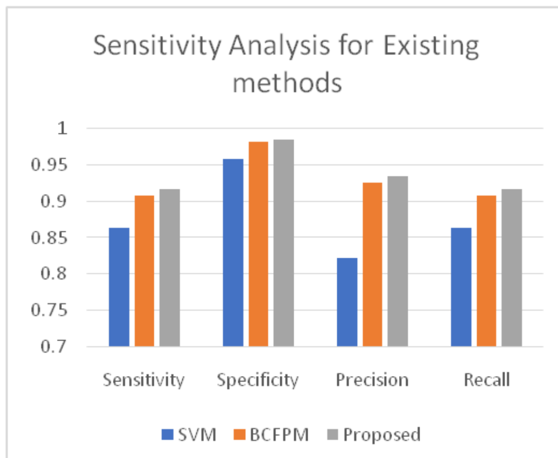

Fig. 4: Comparative analysis among existing and proposed methods based on different parameters

In fig.4 and table 3 results obtained are the comparison of existing techniques like SVM and BCFPM vs. proposed techniques for the performance value. The performance parameters are sensitivity, specificity, precision and recall. On the basis of this graph results showed that for different parameters the performance of proposed technique is highest as compared to others.

Table 4: Comparative analysis among existing and proposed methods based on various parameters

Parameters	SVM	BCFPM	Proposed
Jaccard Coeff	0.94107	0.96785	0.97142
Dice Coeff	0.96964	0.98366	0.9855
Kappa Coeff	0.754	0.8085	0.8299
Accuracy	0.81	0.91	0.92
F-Measures	0.8421	0.91666	0.92592

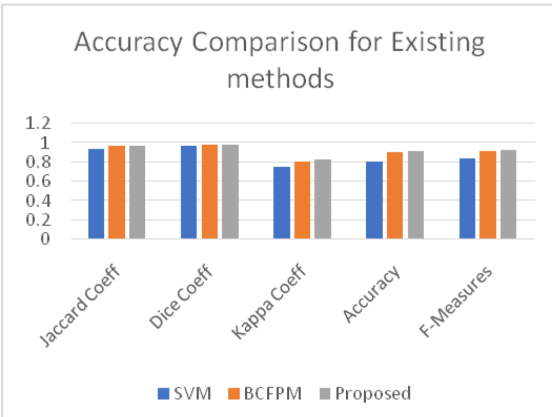

Fig. 5: Comparative analysis among existing and proposed methods based on various parameters

In fig.5 and table 4 results obtained are among the existing like SVM and BCFPM and proposed method based on Jacard Coefficient, dice coefficient, Kappa coefficient, accuracy and F-measures. On the basis of these results showed that for different parameters the performance of proposed technique is better as compared to other.

Table 5: Sensitivity Analysis for Neural Network Techniques

Parameters	KNN	Bayesian	Proposed
Sensitivity	0.93137	0.92233	0.99029
Specificity	0.98139	0.98135	0.99766
Precision	0.92233	0.92233	0.99029
Recall	0.93137	0.92233	0.990291

In fig.6 and table 5 results obtained are the comparison graph of sensitivity analysis among existing KNN, Bayesian vs. proposed techniques for the performance value. On the basis of this graph results showed that for different parameters the performance of proposed technique is highest as compared to others.

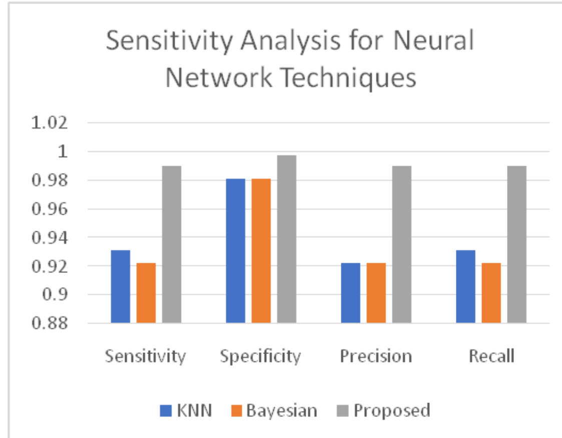

Fig. 6: Sensitivity Analysis for Neural Network Techniques

Table 6: Accuracy Analysis for Neural Network Techniques

Parameters	BCFPM	SVM	Proposed
Jaccard Coeff	0.9718	0.96992	0.99624
Dice Coeff	0.9857	0.98473	0.99811
Kappa Coeff	0.8088	0.811	0.8214
Accuracy	0.9	0.92	0.99
F-Measures	0.92682	0.92233	0.990291

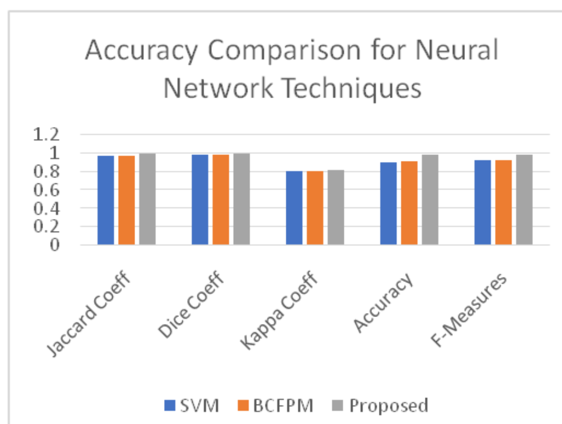

Fig. 7: Accuracy Analysis for Neural Network Techniques

In fig.7 and table 6 results obtained are the comparison graph of accuracy analysis among existing KNN, Bayesian vs. proposed techniques for the performance value. On the basis of this graph results showed that for different parameters the performance of proposed technique is highest as compared to others.

CONCLUSION

This paper presented the enhanced model of data prediction for improving the performance of virtual HMI system. The work is mainly aim to match the sensor data with an optimal pattern and clustering using the EDP method. The data prediction system is performed by the BDP combined with the Neural Network. With this system, first the pre-processed feature is matched with the pattern by using BDP-NN to find the type of data without directly passed into the whole dataset. From that type identified result, the similarity between the matched result and overall dataset is retrieved by using the EDP method to display all matched result from the bulk dataset with better classification result. To analyse the performance of prediction and the overall HMI model compared with traditional model of data prediction techniques.

Several issues with time and cost comparisons and calculations will need to be addressed in future work.

ACKNOWLEDGMENT

A heartfelt thanks are conveyed to Professors, North East Frontier Technical University, Medog, Aalo, Arunachal Pradesh., by authors for providing them with the mandatory facilities to complete the project effectively.

REFERENCES

[1] Chen LS, Liu CH, Chiu HJ (2011) A neural network-based approach for sentiment classification in the blogosphere. J Informetr 5(2):313–322

[2] X. Liu, X. Zhu, M. Li, L. Wang, C. Tang, J. Yin, D. Shen, H. Wang, W. Gao, late fusion incomplete multi-view clustering, IEEE Trans. Pattern Anal. Mach. Intell. 41 (10) (2019) 2410–2423.

[3] L. Zhang, Q. Zhang, B. Du, X. Huang, Y. Y. Tang, D. Tao, Simultaneous spectral-spatial feature selection and extraction for hyperspectral images, IEEE Trans. Cybern. 48 (1) (2018) 16–28.

[4] L. Song, C. Wang, L. Zhang, B. Du, Q. Zhang, C. Huang, X. Wang, Unsupervised domain adaptive re-identification: Theory and practice, Pattern Recognition. 102 (2020) 107173.

[5] D. Tolic, N. Antulov-Fantulin, I. Kopriva, A nonlinear orthogonal non-negative matrix factorization approach to subspace clustering, Pattern Recognition. 82 (2018) 40–55.

[6] Y. Meng, R. Shang, F. Shang, L. Jiao, S. Yang, R. Stolkin, Semi-supervised graph regularized deep nmf with bi-orthogonal constraints for data representation, IEEE Trans. Neural Networks Learn. Syst. PP (2019) 1–14.

[7] Cai C, Xia B (2015) Convolutional neural networks for multimedia sentiment analysis. In: 4th Springer conference on natural language processing and Chinese computing, pp 159–167

[8] Bo Yang, Xiao Fu, Nicholas D Sidiropoulos, and Mingyi Hong. Towards k-means-friendly spaces: Simultaneous deep learning and clustering. arXiv preprint arXiv:1610.04794, 2016.

[9] Peihao Huang, Yan Huang, Wei Wang, and Liang Wang. Deep embedding network for clustering. In Pattern Recognition (ICPR), 2014 22nd International Conference on, pages 1532–1537. IEEE, 2014.

[10] Pan Ji, Tong Zhang, Hongdong Li, Mathieu Salzmann, and Ian Reid. Deep subspace clustering networks. In Advances in Neural Information Processing Systems, pages 23–32, 2017.

[11] René Vidal. Subspace clustering. IEEE Signal Processing Magazine, 28(2):52–68, 2011.

[12] Ehsan Elhamifar and René Vidal. Sparse subspace clustering. In Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on, pages 2790– 2797. IEEE, 2009.

[13] Shankar R Rao, Roberto Tron, René Vidal, and Yi Ma. Motion segmentation via robust subspace separation in the presence of outlying,

incomplete, or corrupted trajectories. In Computer Vision and Pattern Recognition, 2008. CVPR 2008. IEEE Conference on, pages 1–8. IEEE, 2008.

[14] Chih-Chung Hsu and Chia-Wen Lin. Cnn-based joint clustering and representation learning with feature drift compensation for large-scale image data. IEEE Transactions on Multimedia, 20(2):421–429, 2018.

[15] Jürgen Schmidhuber. Deep learning in neural networks: An overview. Neural networks, 61:85–117, 2015.

[16] Poria S, Peng H, Hussan A, Howard N, Cambria E (2017) Ensemble application of convolutional neural networks and multiple kernel learning for multimodal sentiment analysis. Neurocomputing 261:217–230

[17] R. Shang, Y. Meng, W. Wang, F. Shang, L. Jiao, Local discriminative based sparse subspace learning for feature selection, Pattern Recognition. 92 (2019) 219–230.

[18] Y. Zhang, Z. Zhang, S. Li, J. Qin, G. Liu, M. Wang, S. Yan, Unsupervised nonnegative adaptive feature extraction for data representation, IEEE Trans. Knowl. Data Eng. 31 (12) (2019) 2423–2440.

[19] Sudipto Guha, Rajeev Rastogi, Kyuseok Shim, (2015) "ROCK: A Robust Clustering Algorithm for Categorical Attributes", International Journal of Science, Engineering and Technology Research (IJSETR), 2015.

[20] Hemmatian, F., Sohrabi, M.K. (2019) "A survey on classification techniques for opinion mining and sentiment analysis", Artificial Intelligent Rev 52, 1495–1545.

[21] Borele, P., Borikar, D.A. (2018) "An approach to sentiment analysis using artificial neural network with comparative analysis of different techniques", IOSR J. Comput. Eng. (IOSR-JCE) 18(2). e-ISSN: 2278-0661, p-ISSN: 2278-8727

[22] Ebrahimi M, Suen CY, Ormandjieva O (2016) Detecting predatory conversations in social media by deep convolutional neural networks. Digit Investig 18:33–49