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RESEARCH ARTICLE

Multi Self-Organizing Map (SOM) Pipeline Architecture for Multi-View Clustering

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ABSTRACT Clustering has proved to be a successful classification method when it comes to dealing with multiview data. Each method and technique tries to achieve efficiency and accuracy in classifying the multiview data. Multi-source data contains noise and divergence. Another problem is that each view contains many features, so usually the multiview dataset is multi-dimensional. This raises basic problems like the need for a dimensionality reduction technique for optimal selection of features, fusing the data of different views, and maintaining the inter- and intra-consensus of the multiview dataset. The fusion technique should merge the complementary information efficiently. The goal of this study is to use a promising technique for dimension reduction that reduces the noise but maintains the inter-view and cross-view consensus. A self-organizing map is one of the well-known unsupervised neural network algorithms used for preserving typologies during mapping from the input space (high-dimensional) to the display (low-dimensional).An algorithm called Local Adaptive Receptive Field Dimension Selective Self-Organizing Map 2 is a modified form of a self-organizing Map to cater different data types in the dataset. It calculates the dimension relevance with various data instances. These further place the relevant dimension samples in one group. The method does not need to know the number of clusters before hand, as it dynamically determines it during the process. Finally, this study proposed a novel multi-view learning framework that analyzes multi-source data and generates fine clusters efficiently.

INDEX TERMS Self organizing map, multiview, clustering, classification, pipeline.

I. INTRODUCTION

Any information that has multiple production or representation is known as multi-view data. For example, flood disaster reports are published by many new channels in the area. Each channel represents information about the same incident. So here the targeted area of the information is the same but it is produced and represented by each channel either similarly or differently. Therefore in this Era of big data, there are many other multi-source and multi-view real-world examples like multimedia content: video with audio, an image with caption and written script in a different format, or handwriting a web page with meta tags, textual and contextual information, etc.

Using single-model learning algorithms to explore multi-source data is inappropriate. In a uni-modal approach, all the views will be combined to analyze as a single unit of study. As the multi-source data is heterogeneous, each view is considered as a different domain. Multiview analysis deals with partitioned and sample data. Each sample contains features that are different in each view. So, the value of each sample in the view is calculated to specify the role of the view in analyzing Multiview data. Hence, each view is weighted differently, participating more or less in the knowledge discovery hunt. Moreover, a lot of recent work

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done in this field proves the superiority of multi-modal learning approaches over uni-modal learning. The multi-model methods achieve much better accuracy and efficiency as compared to uni-model methods.

Due to the fact that a large number of applications today use unsettling, highly diverse information sources, it becomes necessary to effectively handle and analyze the information gathered in order to uncover and make use of hidden knowledge. Numerous techniques for machine learning have explored the possibilities of Multiview data analysis. In the area of multiview knowledge discovery, there is still opportunity for development.

Multi-view classification techniques are divided into two major categories: supervised and unsupervised. Although some proposed methods also work on hybrid approaches. The supervised method does not work well on large-scale multi-domain data. In an unsupervised approach, the main focus of this study is clustering. Clustering is the unsupervised method of grouping a set of data objects into multiple groups, so that the objects within a cluster have high similarity, but are very dissimilar to the objects in other clusters. Many Multi-view clustering approaches have been proposed so far. The categorization of these methods is done based on their operation mechanism. In this study, clustering has been divided into four categories.

- Graph-based Multiview clustering.
- Kernel-based Multiview clustering
- Subspace-based Multiview clustering
- Deep-learning based Multiview clustering

For multi-view clustering, graph-based methods draw multiple graphs and try to form a connection or network between these graphs using different approaches. Some methods use a similarity matrix to trace similar data nodes between different graphs. A unified graphs matrix is another approach to trace the uniformity between different graphs. The fusion process fuses the information from each view and uses different network-based or spectral methods to extract the Knowledge clusters from it. Some researcher adds a clustering step to produce final clusters. Some other uses are pre-fusion clustering for anchor point or centroid initialization.

To address the issue raisd in [1], a novel approach called One Step Multiview Spectral Clustering (OMSC) has been introduced. In this technique, the low dimensional feature space and optimal affinity matrix are learned in an iterative manner improving the quality of resultant clusters. The auto-weighted technique is used to rank views according to their usefulness i.e., high values for more useful views and low ranks for less useful views. Another graph-based system called Graph-based Multiview Clustering (GMC) [2] is proposed. Different Hyper Parameters have a vital impact on the final clustering result. They can be the regularization parameter for the weighting scheme or threshold values. In an ideal case, we will have no hyper Parameters involved. An effort was done by Wang et al. [3] in the structured graph same direction. They proposed two parameter-free approaches for Multiview clustering. One is named Divisor weighted Multi-view Projected Clustering (DwMPC) where divisor weights are assigned to different views and the other is called Self-weighted Multi-view Projected Clustering (SwMPC).

A spectral embedding space is used by the researcher to generate noise and redundancy-free low dimensional space. The inner product of the normalized embedded matrix is used in the third-order tensor [4]. The real-world multi-view data contain high divergence. Divergence not only indicates the noise and corruption but also the view-specific data that is undesirable for consistent learning among multiple views [4]. In 2021 research [5] a unified framework called Consistent and Divergent Multi-view Graph Clustering (CDMGC) is presented. The approach addresses the fused graph diversity problem by separating consistent and divergent parts. Dealing with large-scale data is another problem of Multiview real-time applications. Huge data may directly affect the execution and processing speed of clustering systems. To increase the system efficiency, researcher in [6] introduced a novel spectral clustering approach using bipartite graphs (MVSC). This method forms a bipartite graph between chosen centroid called the silent point and the data node. It generates final clusters using the K-mean algorithm. Maintaining view consensus information is also important for generating unbiased clustering results [7]. Bipartite Graph-based Multiple-view Clustering (BIGMC) generates initial anchor points using a clustering algorithm to represent each view consensus. An efficient joint learning framework using a bipartite graph is presented.

Method of Multiview machine learning and data extraction is necessary to understand the characteristics of multiview data. Each view is a multiview data set consisting of multiple features. So, the Multiview dataset usually contains high-dimensional data. Each view in the Multiview data set is a complete source of information, containing sufficient knowledge. Combining several points of view reveals hidden patterns in multi-source data while also producing complimentary information.

Let's say a multi-view dataset consists of three views: V1, V2, and V3 as shown in Figure 1. The information that is shared by two or more views shows the underlying information, which is called the consensus of two or more views. The unshared part may contain two types of data: complementarity information and divergent information. This is the view-specific information that may complement and support some information, i.e., increasing the accuracy. Divergent information is contradictory information between multiple views. The data can be noisy and the noise can be a machine error, faulty information, redundant data, or a piece of incomplete information.

A. OBJECTIVE OF STUDY

The objective of this study is to comprehend a comprehensive review of modern developments in the field of multiview

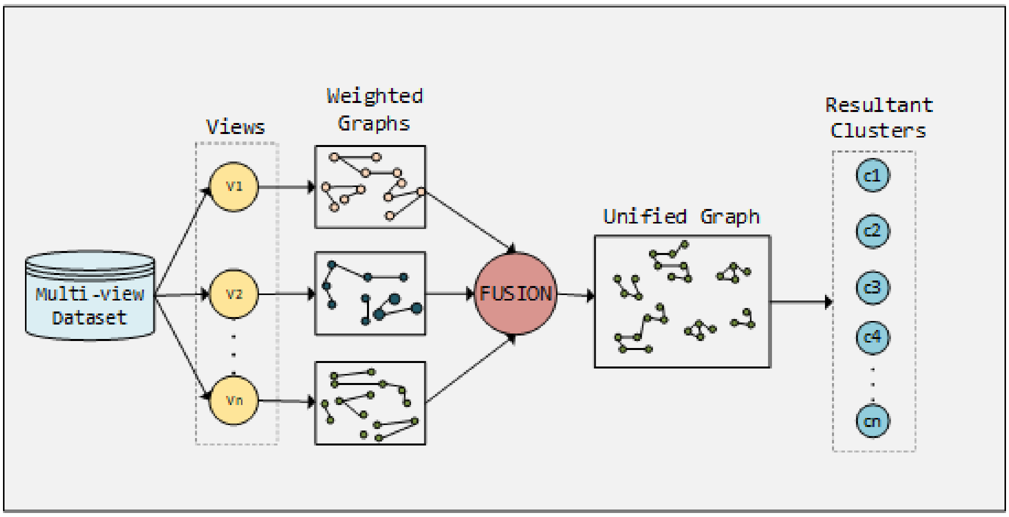

FIGURE 1. Generalized graph-based multiview clustering model.

clustering. Secondly, incorporate the state of art proved dimensionality reduction technique to handle diversity and noise. The main objection is to design a novel efficient framework for Multiview clustering without the loss of consensus information among each view.

B. MAJOR CONTRIBUTION

Clustering has proven its significance in the field of Multiview unsupervised classification. The main purpose of the study is to maintain the underlying relationship among multiple views while reducing dimensionality and fusing the complementary information present in them in an efficient manner. There is still a need for a more optimized and improved solution.

C. MOTIVATION OF THE STUDY

Clustering has proved to be a successful classification method when it comes to dealing with Multiview data. Each method and technique tries to achieve efficiency and better accuracy for classifying the Multiview data. Multi-source data is full of noise and divergence. Another problem is each view contains many features, so usually, the Multiview dataset is high dimensional, which raises the following basic problems.

- There is a need of a dimensionality reduction technique for optimal selection of features.
- While fusing the data of different views, the inter and intra-consensus of the Multiview dataset should be maintained.
- The fusion technique should merge the complementary information efficiently.

D. ORGANIZATION OF STUDY

The rest of the article is organized as follows: Section II presents a literature review. The proposed methodology is presented in Section III. The results are discussed in Section IV. Section V describes the experimental dataset, and Section VI presents the conclusion of the study.

II. LITERATURE REVIEW

In Multiview datasets, each view contains view-specific information. Integrating all the views with similar weights may affect the final results, This study [8] presents experiment on rectal cancer and human colon datasets with view-specific weights with the Multiple Kernel Learning (MKL) algorithm. The algorithm shows the individual importance of each view in the Multiview dataset. Extended K-mean clustering algorithm in Kernel space incapable of finding arbitrary shaped clusters [9]. However, kernel initialization choice still highly affects the clustering results. Determining L (2,1) norm for distance measurement between the node and its centroid. The Robust Multi kernel K-Mean algorithm (RMKKM) increases the overall robustness of the system [9].The researcher in [10] used a novel kernel-based ranking technique that completely excludes uninformative views but keeps the less informative contributors. Furthermore, two different model approaches are proposed. Multi-View Kernel k-means (MVKKM) used a distance-based scheme for model training and Multi-View Spectral Clustering MVSpec used a trace-based spectral method to reduce the intra-cluster variation. By considering the neighborhood structure of the multiple-derived kernel, the clustering performance can be can highly improve [11]. The researcher proposed a three-step procedure to construct kernel neighbour structure. First, find the neighbour node using K-nearest in kernel space. Secondly, construct the neighbouring structure through space metric and finally normalize and group through subspace segmentation. To increase multiple kernel diversity, [12] uses matrix-induced regularization. The cost function is used to measure the co-relation between each pair of kernels in the dataset. Hence the approach leads to better clustering results. The fusion of multiple kernels and high optimization

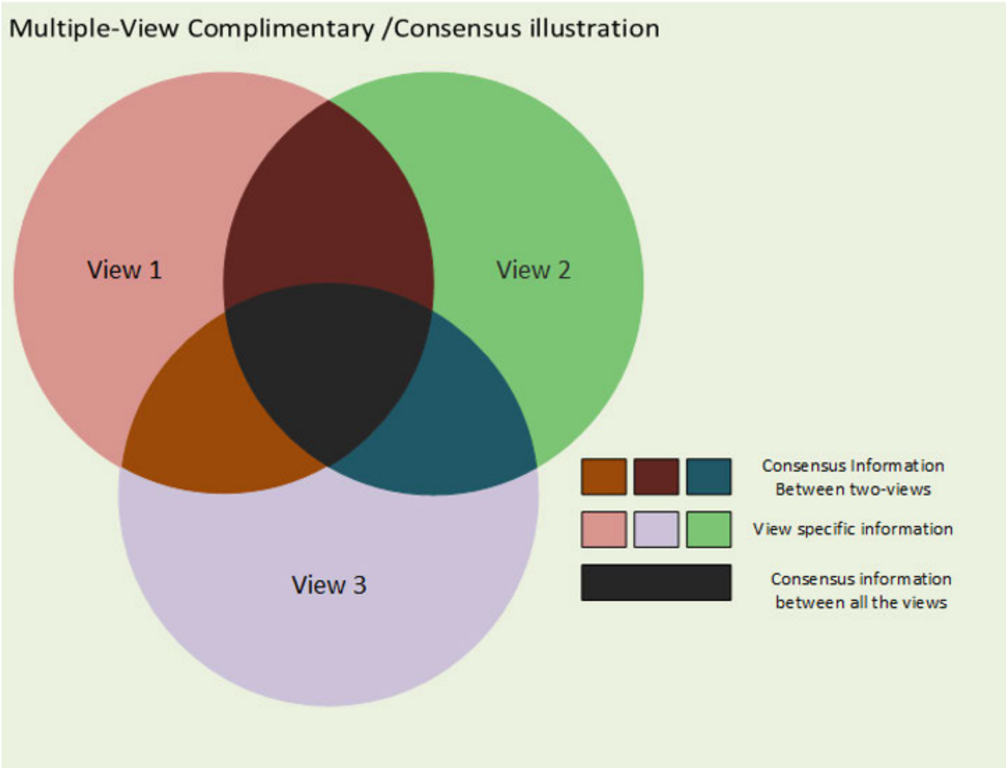

FIGURE 2. Complementary information among multiple views.

increases the computational complexity of the system. Therefore, most of the procedures are difficult to understand. Multi-view Clustering via Late Fusion Alignment Maximization (MVC-LFA) deals with the complexity issue by increasing alignment between weighted basic partitions. The results show a significant improvement in clustering results.

Most subspace methods use a separate affinity matrix for each view in the Multiview dataset. An alternative method was presented by [13], that uses joint subspace by constructing a shared affinity matrix. The unified matrix is shared among all the views in the multiple view dataset. The approach is named Multi-view Low-rank Sparse Subspace Clustering (MLRSSC). The Learning Process of hidden representation from an individual view normally affects the original structure of data within that single view. This may cause the loss of valuable structural information. Zhang et al. [14] proposed a novel Latent Multiview Subspace clustering method. The method learns and exposes the common features from the latent space and represents them in a common subspace. The architecture in [15], prevents the underlying data structure through Alternating Direction Minimization Method (ADM) optimization approach. The method is called Flexible Multiview Representation (FMR). It uses Schmidt Independence Criterion (HISC) to get the nonlinear, high-order relation between multiple views to uncover hidden clustering data structures. The Consensus One-Step Multi-View Subspace Clustering (COMVSC) [16] is a novel method proposed to eliminate the effect of noise by optimally integrating each partition information in Multiview Subspace Clustering. An iterative learning method claims to preserve the local view structure and jointly learn each partition. The researcher [17] uses the two-layer approach to recover the hidden low-dimensional subspace and identity relationship between different views. This approach is called Reciprocal Multi-layer Subspace Learning (RMSL). In the first layer, the Hierarchical Self-Representative HSRL method is used to identify hidden relations among the different views whereas in the second layer, Backward Encoding Network (BEN) is used to explore the complex relationships between all the views in multiple views. This method led to a more efficient and optimal display of the relationship between data in different views. The author in [18] represents the soft clustering approach using an enhanced version of Self Organizing Maps (SOM). The structure used is called a time-varying structure. Both the topological structure of latent space and the final number of clusters is determined through the thought process. Clusters are created by calculating dimension relevance based on network-learned relevant features. The relevance is compared by setting the threshold value. The method is called Local Adaptive Receptive Field Dimension Selective Self Organizing Map 2 (LARFDSSOM2), which is the enhanced version of LARFDSSOM [19]. The main disadvantage of this approach is the need for parameter

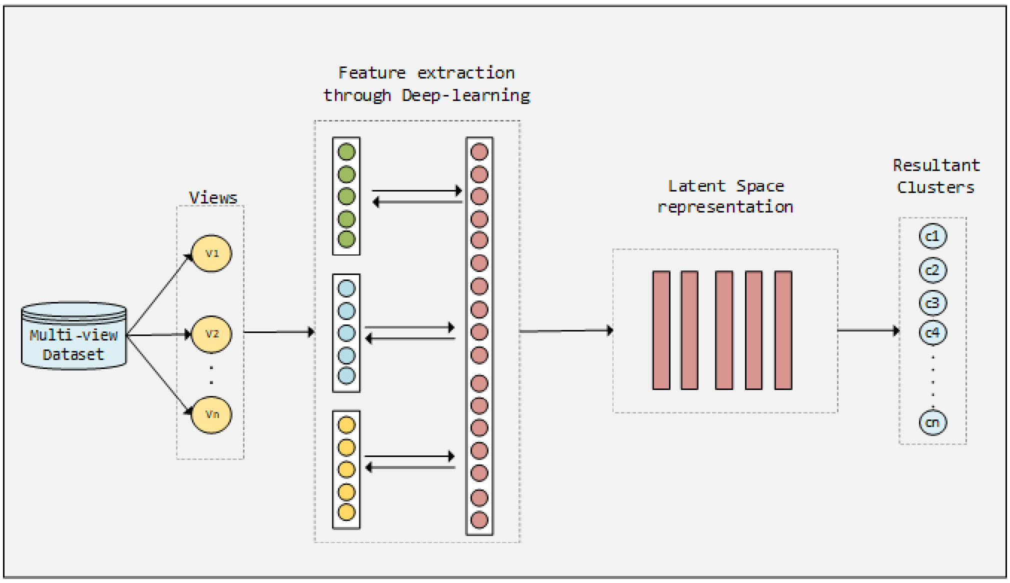

FIGURE 3. Generalized subspace-based multiview clustering model.

tunning to increase clustering accuracy. Split Multiplicative View Subspace Clustering (SMSC), proposed by [20], used to extract components that are consistent with the subspace structure. These valuable components from each view will preserve the consensus structure of the subspace.

Multi-view Spectral Clustering Network (MvSCN) [5] claimed to be the first spectral-based deep approach. Here the author uses deep metrics for learning views local in variance instead of computing pairwise similarity. The method works well on real-world large-scale datasets. Another approach is to use subspace learning with a self-representation matrix [21]. The method called Multi-view Deep Subspace Clustering Network (MvDSCN) is a network-building approach. It creates two networks called Diversity Network (Dnet) and Universality Network (Unet). Dnet forms self-representation matrices for all the views in the Multiview dataset whereas Unet learns a common representation matrix for each of the views in the Multiview dataset. One of the popular approaches for clustering high-dimensional data is Non-negative Matrix Factorization (NMF) [22], [23]. A novel fusion approach is adopted by the researchers [22], [24]. Later decomposed matrices are fused to learn a common partition. Joint optimization strategies such as Deep multi-view Joint Clustering (DMJC) [25] overcome the disadvantages of disjoint learning strategies. The major disadvantage of disjoint learning are that it ignores the underlying relationship between feature selection and clustering. To handle the nonlinear correlation among different views of a multi-view dataset, Deep Adversarial Multi-view clustering (DAMC) [26] network is proposed. This method generates the discriminator network using a deep autoencoder for each view. The network perceives the data distribution and untangles the latent space. Appropriate parameter selection also plays a vital role in simple clustering as well as in Multiview clustering. Authors [27] proposed a novel method that learns parameters without involving any intensive parameter selection procedure. The method is called Cross-view Matching Clustering (COMIC). It plots data points of each view in projection space. Each data point should satisfy two properties that are Geometric Consistency (GC) for normalizing connections between data points and Cluster Assignment Consistency (CAC) to minimize the connection discrepancy of the graph. To retain consistency among multiple views, it is essential to learn view-specific information. The joint learning model called Autoencoder in Autoencoder Networks (AE2-Nets) [28] is proposed. The framework extracts each view's inner information through the inner autoencoder whereas the outer autoencoder model degradation procedure encodes fundamental information of each view to form a common complete representation. The model evaluates the derived representation using the K-mean algorithm for clustering.

Almost all the methods, no matter what category they belong to, strive to achieve better clustering results while increasing overall clustering performance. Few algorithms emphasize the feature selection and dimensionality reduction problem. However, through efficient feature selection, redundant data such as noise can be avoided.

III. PROPOSED METHDOLOGY

A model has been designed and presented in Figure 4. The model represents the basic pipeline architecture using multi-SOM. The model has been implemented and tested for performance evaluation. When data is high dimensional, conventional methods to measure object distance can be affected. Two methods are introduced to handle the dimensionality issue: The Subspace clustering and Dimensionality reduction techniques. In some applications, objects of data may consist

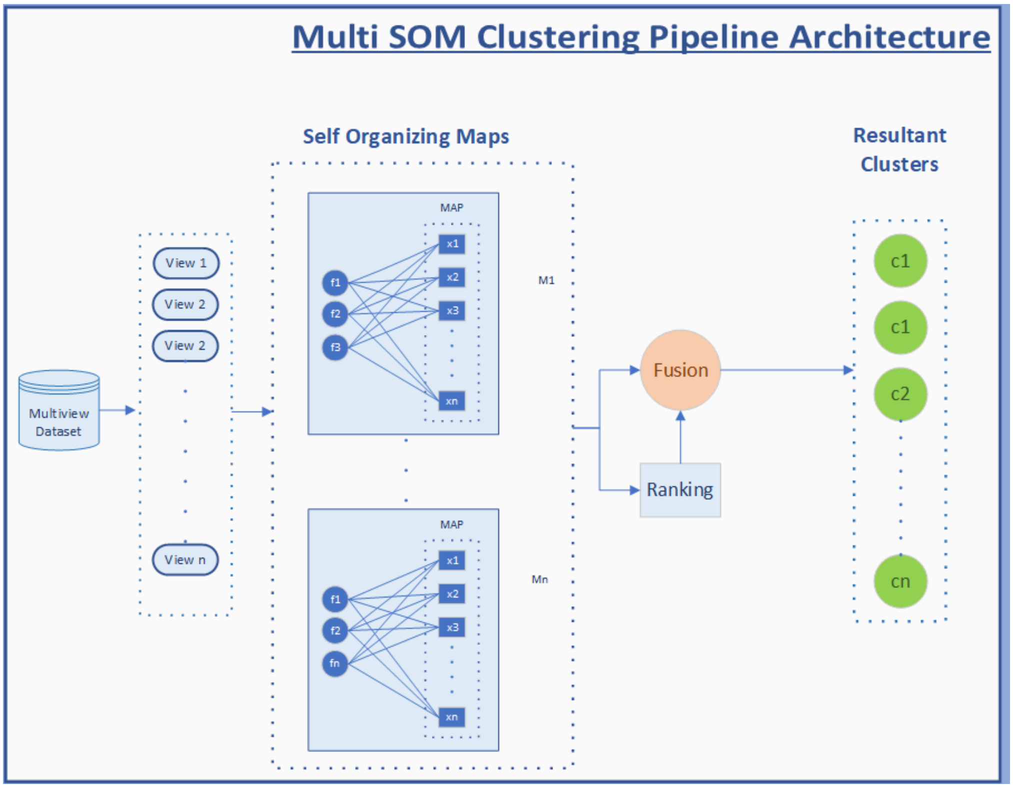

FIGURE 4. Proposed multi SOM architecture for multi-view clustering.

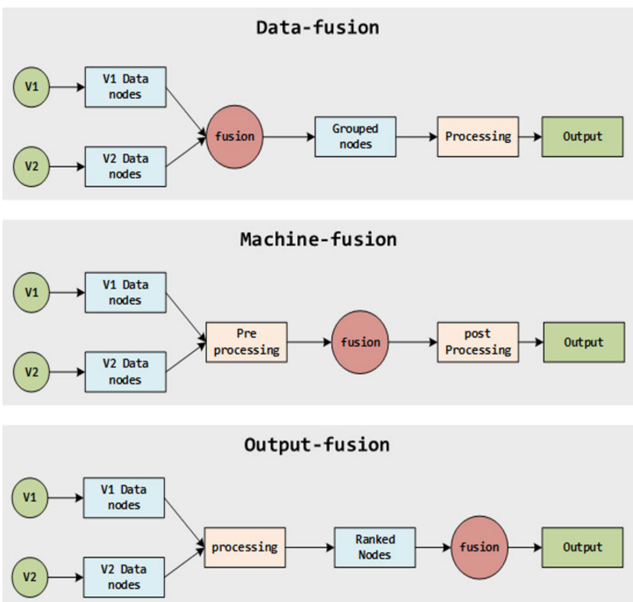

FIGURE 5. Types of fusion processes.

of 10 attributes or more than that, such objects are referred to as high dimensional data space. High-dimensional data space can either be messy or big. Subspace Clustering methods find clusters that exist in the subspace of the given high dimensional data space where subspace is part of attributes of full space. A good clustering algorithm should have the ability to discover a cluster of arbitrary shapes. Clusters can have any shape, not only spherical. So, a good clustering algorithm should be able to detect any shape clusters. Some application needs to have the related domain knowledge or parameters for example the number of clusters required. Sometimes these parameters are hard to determine because of high dimensionality or the need for deep domain knowledge requirements that burden users and make quality control difficult. Robust-to-noise algorithms are needed. Incremental clustering and insensitivity to input order are required. Incremental data is where newer data may arrive at any time. Some algorithms need to recompute clusters from scratch on the arrival of new data or data updates. Most algorithms work with low-dimensional data where data may have 2 or 3 dimensions only. High dimensionality is needed to be handled well in Multiview clustering problems.

Different algorithms use different cluster separation theories. Each data entry or object should belong to one and only one cluster or in some algorithms, it may belong to many cluster groups. The similarity between objects within clusters can be measured differently using Euclidean space, density, and contiguity. Cluster search space can vary, one can search the whole data space for searching clusters. This approach is good for low-dimensional data sets. With high dimensional data, such an approach may not work as full space clusters meaning unreliable similarities. In such a case, it is better to divide the entire space into smaller low-dimensional subspaces.

```
Input:    Dataset X of n number. of views V1 …. Vn
Output:   Fine final Clusters with labels Y
foreach V in X do
        Split V data with 80/20 ratio for training and testing respectively
        Train V
        Classify V test data
        return SOM_Classified data
end
foreach V in (SOM_Classified data) do
        Generate segments
        return Segmented Views (Sv) data
end
foreach s in Segmented Views do
        Fuse segments
        return Fused Data
end
foreach node x in Fused Data do
        Generate Final Clusters c
        return Final Clusters
end
```

FIGURE 6. Algorithm I MSOMPA$_M V$.

TABLE 1. Statistics of real-time datasets.

Dataset	View	Class	Sample	Dimension					
				V1	V2	V3	V4	V5	V6
YaleB	3	10	650	2500	3304	6750			
WebKB	3	4	203	1703	230	230			
MFeat	6	10	2000	216	76	64	240	47	
Caltech20	6	20	2386	48	40	254	1984	512	928
Caltech7	6	7	1474	48	40	254	1984	512	928
100Leaves	3	100	1600	64	64	64			
3Sources	3	6	3560	3631	3068				

A. FUSION OF SELF-ORGANIZING MAPS

Fusion is the process of combining multiple views. The information should be merged in a way that maintains the underlying relationship between the data nodes avoiding noise. Each view can be seen as a separate domain. The fusion process tends to ensemble each domain's knowledge to produce high-quality accurate results. During the learning process fusion can be done at different times, depending upon the strategy followed.

An early fusion that is done directly on data nodes in the input space, is called data fusion. After pre-processing the data, combining knowledge extracted from individual domains instead of raw data is machine fusion. The last one is late fusion, which is done in output space by combining similar data nodes and is called aggregation.

B. SELF-ORGANIZING MAP FOR MULTIVIEW CLUSTERING

Various unsupervised subspace learning methods are applied to different fields to cater high dimensional data space. Popular machine learning techniques are employed such as spectral algorithms, statistics, and algebraic algorithms. One of the popular category is Neural Networks (NN). Self-Organizing Map is one of the well-known unsupervised Neural Networks algorithms. It preserves the topologies during mapping from the input space (high-dimensional) to the display (low-dimensional).

An algorithm called Local Adaptive Receptive Field Dimension Selective Self-Organizing Map 2 (LARFDS-SOM2) is the modified form of an organizing Map to cater different data types in the dataset. It calculates the dimension relevance with various data instances. These further places the relevant dimension samples in one group. The method does not need to know the number of clusters beforehand as it dynamically determines it during the process.

C. RANKING METHOD AND ALGORITHM

Dun Index is the well-known Cluster Validity Index used to check the goodness of clusters. It is used to calculate the

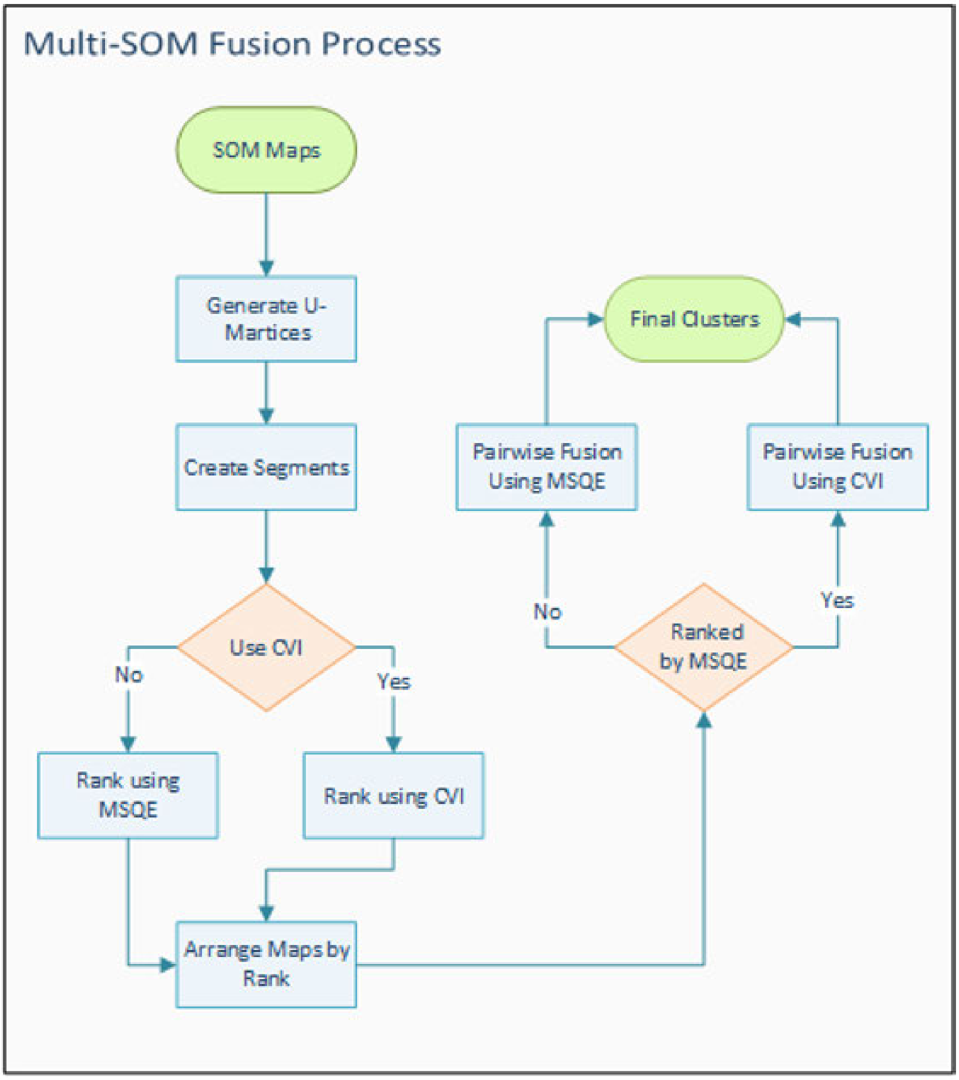

FIGURE 7. Data flow for fusion among multiple SOM.

TABLE 2. Performance comparison Yale B.

Methods	ACC	ARI	NMI	F-Score	PRE	Recall
MVCC	0.196±0.00	0.157±0.00	0.157±0.00	0.148±0.00	0.118±0.00	0.197±0.00
P-MLRSSC	0.481±0.08	0.157±0.00	0.378±0.04	0.302±0.02	0.249±0.01	0.430±0.02
C-MLRSSC	0.434±0.00	0.157±0.00	0.399±0.02	0.322±0.01	0.249±0.01	0.455±0.02
GMC	0.434±0.00	0.157±0.00	0.399±0.02	0.265±0.00	0.204±0.00	0.378±0.00
MVGL	0.300±0.00	0.093±0.00	0.271±0.00	0.204±0.00	0.164±0.00	0.270±0.00
MVSC	0.468±0.00	0.147±0.00	0.431±0.00	0.261±0.00	0.193±0.00	0.405±0.00
MLAN	0.575±0.01	0.090±0.00	0.348±0.00	0.118±0.00	0.157±0.00	0.321±0.00
BIGMC	0.575±0.01	0.244±0.020	0.525±0.01	0.350±0.02	0.268±0.01	0.495±0.02
MSOMPA_MV	0.618±0.04	0.346±0.04	0.46±0.04	0.62±0.04	0.628±0.04	0.62±0.04

internal and external validity of derived clusters. After SOM classification, the multiple views data nodes are ranked using the Dun Index. If the Dun Index drops from the threshold value by adding up the node, the data node will be dropped. After the process of Ranking, the MSOMPA_MV Generate fused clusters using MSQA i.e., Mean Square Error. The threshold value is set. The pairwise comparison is done, if the calculated value passes the threshold, the data node will be dropped, because it is negatively affecting the cluster quality.

D. DATASETS

1) SYNTHETIC DATASETS

For the evaluation of the proposed Multi Self-organizing maps pipeline architecture, we used two synthetic Datasets

```
Input:     Segmented Dataset S {S1 .... S m} of each view V {V1 ....... Vn }
Output:    Fused dataset
while Len(S)! =0 do
    foreach Si in V do
        Calculate Dun Index
        Set threshold Value
        for node x in Si do
            Calculate Dun Index dropping x
            If (dun Value >= Threshold Value) do
                Drop x
            end if
        end for
    end foreach
end while
return fused dataset
```

FIGURE 8. Algorithm 2 Ranking MSOMPA-MV.

TABLE 3. Performance comparison WebKB.

Methods	ACC	ARI	NMI	F-Score	PRE	Recall
MVCC	0.709±0.00	0.468±0.00	0.418±0.00	0.664±0.00	0.708±0.000	0.350±0.03
P-MLRSSC	0.425±0.03	0.246±0.03	0.355±0.03	0.445±0.03	0.663±0.04	0.350±0.03
C-MLRSSC	0.442±0.04	0.266±0.03	0.376±0.03	0.462±0.03	0.682±0.04	0.350±0.03
GMC	0.769±0.00	0.440±0.00	0.435±0.00	0.700±0.00	0.592±0.00	0.858±0.00
MVGL	0.581±0.00	0.083±0.00	0.144±0.00	0.566±0.00	0.423±0.00	0.858±0.00
MVSC	0.567±0.00	0.068±0.00	0.122±0.00	0.668±0.00	0.417±0.00	0.873±0.00
MLAN	0.729±0.00	0.373±0.00	0.402±0.00	0.564±0.00	0.559±0.00	0.831±0.00
BIGMC	0.795±0.00	0.546±0.00	0.540±0.00	0.753±0.00	0.742±0.01	0.914±0.01
MSOMPA_MV	0.782 ± 0.02	0.41± 0.05	0.37 ± 0.06	0.758 ± 0.02	0.75 ± 0.03	0.782± 0.02

TABLE 4. Performance comparison MFeat.

Methods	ACC	ARI	NMI	F-Score	PRE	Recall
MVCC	0.578±0.05	0.255±0.00	0.422±0.00	0.605±0.02	0.322±0.00	0.342±0.00
P-MLRSSC	0.578±0.05	0.548±0.03	0.700±0.02	0.605±0.02	0.473±0.03	0.843±0.02
C-MLRSSC	0.578±0.05	0.559±0.00	0.703±0.00	0.866±0.00	0.484±0.00	0.843±0.00
GMC	0.882±0.00	0.850±0.00	0.905±0.00	0.866±0.00	0.826±0.00	0.909±0.00
MVGL	0.856±0.00	0.832±0.00	0.904±0.00	0.850±0.00	0.789±0.00	0.920±0.00
MVSC	0.703±0.00	0.694±0.00	0.939±0.00	0.728±0.00	0.651±0.00	0.828±0.00
MLAN	0.973±0.00	0.940±0.00	0.831±0.00	0.946±0.00	0.945±0.00	0.947±0.00
BIGMC	0.932±0.01	0.940±0.01	0.910±0.00	0.956±0.00	0.953±0.00	0.966±0.00
MSOMPA_MV	0.870± 0.01	0.834 ± 0.0	0.856 ± 0.0	0.932 ± 0.01	0.926 ± 0.0	0.926 ± 0.0

TABLE 5. Performance comparison Caltech-20.

Methods	ACC	ARI	NMI	F-Score	PRE	Recall
MVCC	0.533±0.00	0.487±0.00	0.564±0.00	0.541±0.00	0.561±0.00	0.530±0.00
P-MLRSSC	0.434±0.02	0.349±0.05	0.487±0.01	0.464±0.04	0.426±0.05	0.512±0.04
C-MLRSSC	0.429±0.02	0.343±0.06	0.477±0.01	0.460±0.05	0.425±0.05	0.503±0.05
GMC	0.456±0.00	0.128±0.00	0.481±0.00	0.340±0.00	0.228±0.00	0.673±0.00
MVGL	0.578±0.00	0.263±0.00	0.576±0.00	0.415±0.00	0.327±0.00	0.567±0.00
MVSC	0.575±0.00	0.260±0.00	0.567±0.00	0.413±0.00	0.325±0.00	0.567±0.00
MLAN	0.525±0.00	0.197±0.01	0.539±0.00	0.371±0.01	0.279±0.00	0.557±0.02
BIGMC	0.611±0.00	0.498±0.01	0.624±0.00	0.557±0.00	0.576±0.01	0.698±0.00
MSOMPA_MV	0.782 ± 0.01	0.732 ± 0.04	0.61 ± 0.02	0.762 ± 0.01	0.768 ± 0.02	0.784 ± 0.01

TABLE 6. Performance comparison Caltech-7.

Methods	ACC	ARI	NMI	F-Score	PRE	Recall
MVCC	0.471±0.00	0.298±0.00	0.464±0.00	0.334±0.00	0.759±0.00	0.334±0.00
P-MLRSSC	0.609±0.08	0.324±0.02	0.500±0.02	0.334±0.00	0.697±0.04	0.414±0.03
C-MLRSSC	0.563±0.05	0.334±0.03	0.497±0.03	0.524±0.02	0.711±0.05	0.416±0.02
GMC	0.692±0.00	0.594±0.00	0.660±0.00	0.722±0.00	0.886±0.00	0.609±0.00
MVGL	0.579±0.00	0.395±0.00	0.558±0.00	0.570±0.00	0.762±0.00	0.455±0.00
MVSC	0.621±0.00	0.436±0.00	0.581±0.00	0.647±0.00	0.667±0.00	0.629±0.00
MLAN	0.780±0.00	0.572±0.00	0.636±0.00	0.737±0.00	0.739±0.00	0.734±0.00
BIGMC	0.785±0.00	0.572±0.00	0.697±0.00	0.797±0.00	0.904±0.00	0.738±0.00
MSOMPA_MV	0.936 ± 0.00	0.862 ± 0.02	0.764 ± 0.01	0.934 ± 0.01	0.934 ± 0.01	0.936 ± 0.01

TABLE 7. Performance comparison 100Leaves.

Methods	ACC	ARI	NMI	F-Score	PRE	Recall
MVCC	0.128±0.00	0.121±0.00	0.552±0.00	0.136±0.00	0.076±0.00	0.653±0.00
P-MLRSSC	0.030±0.00	0.060±0.00	0.442±0.01	0.077±0.00	0.040±0.00	0.771±0.01
C-MLRSSC	0.030±0.00	0.059±0.00	0.440±0.01	0.076±0.00	0.040±0.00	0.770±0.02
GMC	0.824±0.00	0.497±0.00	0.929±0.00	0.504±0.00	0.352±0.00	0.887±0.00
MVGL	0.766±0.00	0.506±0.00	0.893±0.00	0.513±0.00	0.380±0.00	0.789±0.00
MVSC	0.717±0.00	0.318±0.00	0.886±0.00	0.328±0.00	0.205±0.00	0.826±0.00
MLAN	0.873±0.01	0.818±0.01	0.948±0.00	0.819±0.01	0.775±0.01	0.869±0.00
BIGMC	0.921±0.00	0.883±0.01	0.960±0.01	0.882±0.01	0.870±0.02	0.893±0.01
MSOMPA_MV	0.68 ± 0.0	0.468 ± 0.0	0.79 ± 0.0	0.68± 0.0	0.694± 0.0	0.68 ± 0.0

TABLE 8. Performance comparison 3Source.

Methods	ACC	ARI	NMI	F-Score	PRE	Recall
MVCC	0.761±0.01	0.631±0.00	0.698±0.01	0.734±0.00	0.613±0.00	0.823±0.00
P-MLRSSC	0.682±0.05	0.565±0.06	0.594±0.03	0.659±0.05	0.707±0.05	0.619±0.06
C-MLRSSC	0.662±0.07	0.557±0.08	0.595±0.03	0.654±0.06	0.696±0.05	0.619±0.07
GMC	0.692±0.00	0.443±0.00	0.622±0.00	0.605±0.00	0.484±0.00	0.805±0.00
MVGL	0.302±0.00	-0.036±0.00	0.109±0.00	0.339±0.00	0.218±0.00	0.768±0.00
MVSC	0.531±0.00	0.426±0.00	0.541±0.00	0.535±0.00	0.529±0.00	0.628±0.00
MLAN	0.763±0.00	0.571±0.00	0.689±0.00	0.683±0.00	0.609±0.00	0.777±0.00
BIGMC	0.797±0.00	0.661±0.00	0.705±0.00	0.751±0.00	0.718±0.00	0.834±0.00
MSOMPA_MV	0.87 ± 0.01	0.834 ± 0.00	0.856± 0.00	0.932 ± 0.00	0.926 ± 0.00	0.926 ± 0.00

FIGURE 9. Database sample images.

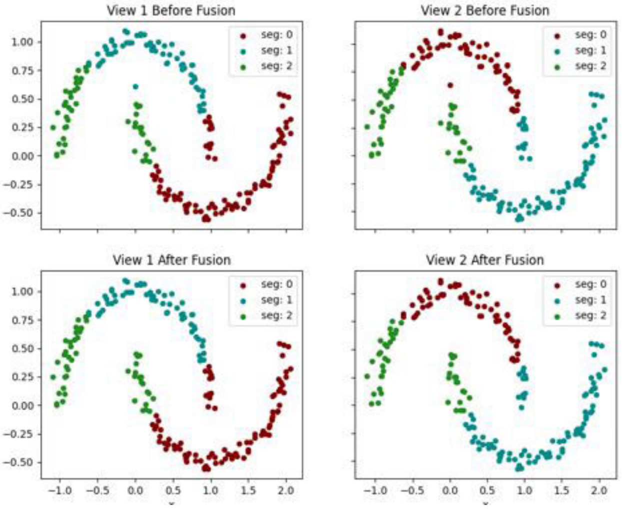

FIGURE 10. Fusion of two view.

called the Two-Moon dataset and the Two-ring Dataset. The two-Moon dataset has two views. Each view has 200 data points. The following setting is being used for two-moon dataset generation.

- No of sample = 200
- No. of views = 2
- Noise = 0.047, 0.056 for view 1 and view 2 respectively.
- Random state = 42

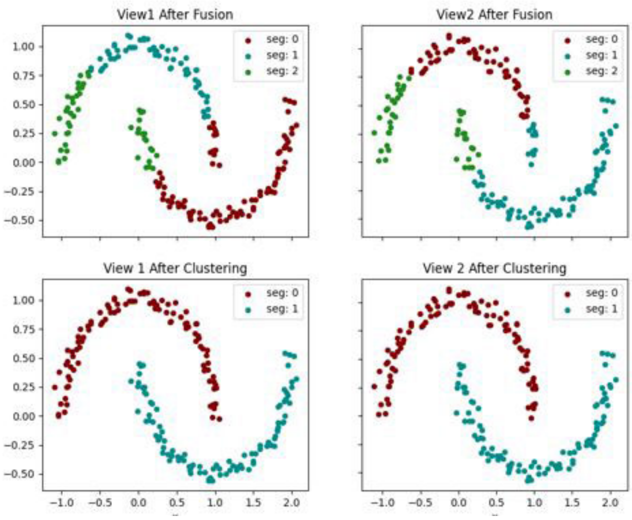

FIGURE 11. SOM final clustering of two views.

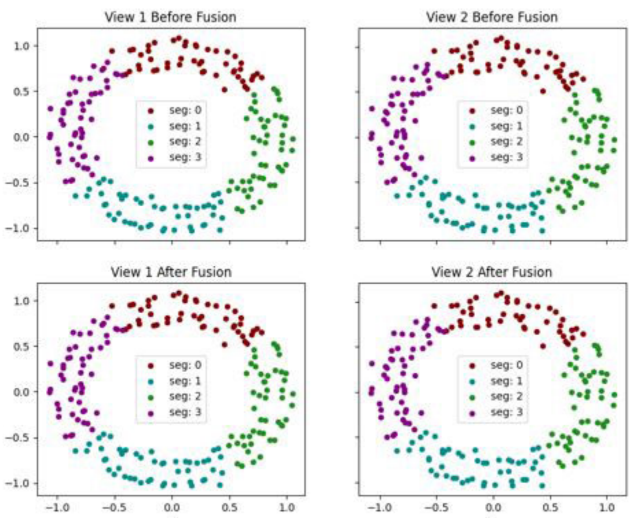

FIGURE 12. Stage 4 fusion of two views i.e., View 1 and View 2 for two-rings datasets before and after fusion views.

The following specifications are used to generate Two-ring dataset:

- No of sample = 200
- No. of views = 2
- Noise = 0.047, 0.056 for view 1 and view 2 respectively.
- Random state = 42

2) REAL TIME DATASETS

The following seven datasets have been used to analyze and compare the performance of the proposed methodology. The detailed Statistics of chosen datasets are stated in Table 1.

1) YaleB. (Extended) [31]
   It is the extended dataset that consists of face images with different expressions.
2) WebKB [32]
   It contains web pages and hyperlinks. They are collected from the computer science departments of four different universities: The University of Texas, Cornell University, The University of Wisconsin, and The University of Washington.
3) Mfeat [30]
   It is the multivariant dataset consisting of handwritten digits (0—9). These are collected from Dutch utility maps.
4) Caltech-20 [29]
   Caltech-20 is the subset of the original caltech101 dataset that contains 101 categories of objects. It contains a subset of twenty categories that are faces, leopards, motorbikes, binoculars, brain, camera, car side, dollar bill, ferry, Garfield, hedgehog, pagoda, rhino, snoopy, stapler, stop sign, water Lilly, Windsor chair, wrench, and yin yang.
5) Caltech-7 [29]
   This dataset is also the subset of the caltech101 dataset of objects. It contains a subset of seven categories which are faces, leopards, motorbikes, dollar bills, Garfield, stop signs, and Windsor chairs.
6) 100Leaves [33]
   It is the one hundred plant species dataset with the shape descriptor, margin, and histogram of texture.
7) 3sources [34]
   The 3source dataset is collected from the famous online sources of news i.e. BBC, The Guardian, and Reuters. It contains 948 different articles about business, health, politics, entertainment sports, and technology.

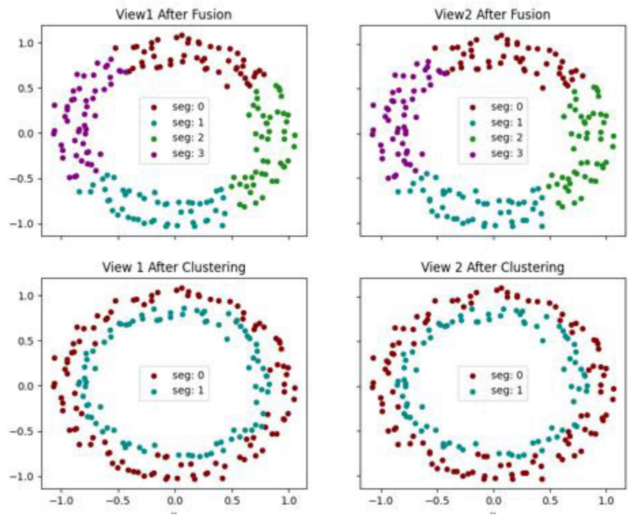

FIGURE 13. SOM final clustering of two views, i.e., view 1 and view 2 for two-rings datasets before and after clustering.

IV. PERFORMANCE PARAMETERS

The machine used for the implementation of Multi Self-organizing map pipeline architecture for Multi-view MSOM-PAMV is stated in Table 5.2. To evaluate the performance results following common matrices are used:

- The Accuracy (ACC)
- The Normalized Mutual Information (NMI)

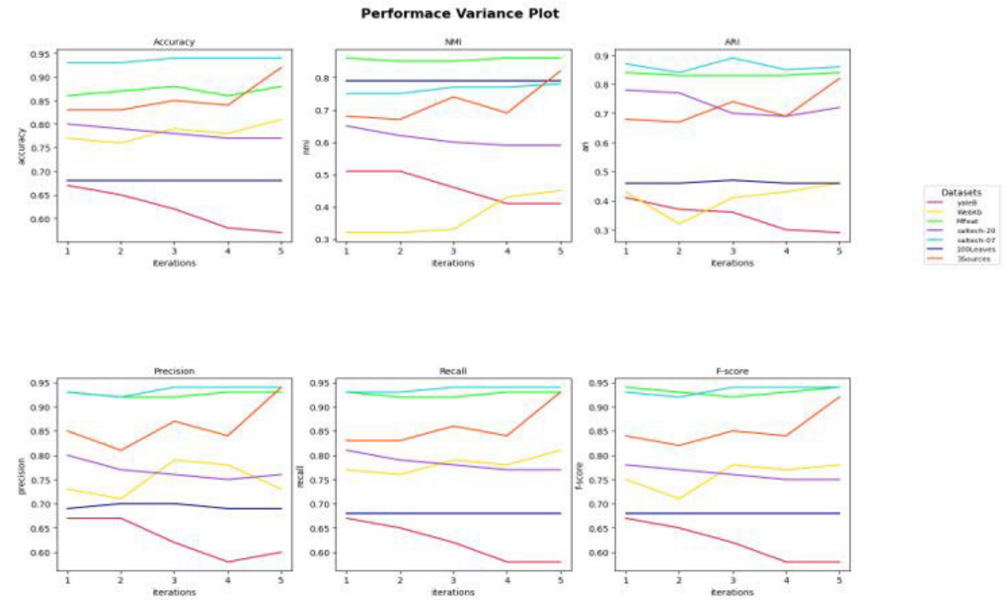

FIGURE 14. Performance variation between five random iterations.

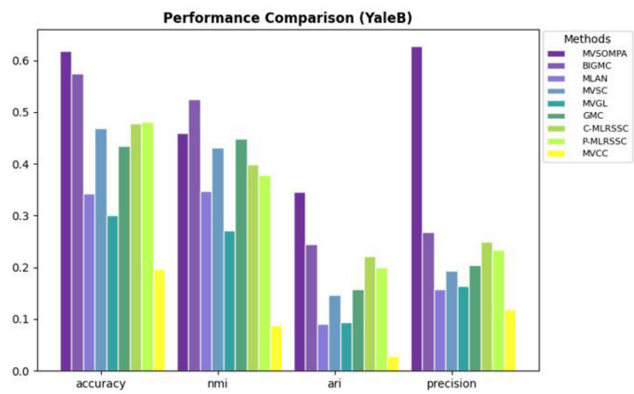

FIGURE 15. Performance comparison with baseline methods (Mean ± Standard deviation) of YaleB extended dataset.

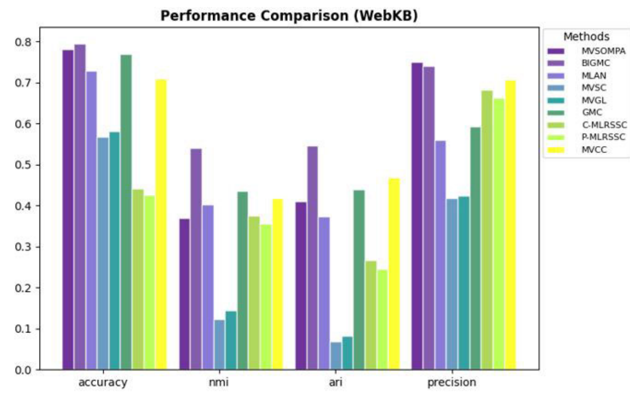

FIGURE 16. Performance comparison with baseline methods (Mean ± Standard deviation) of WebKB dataset.

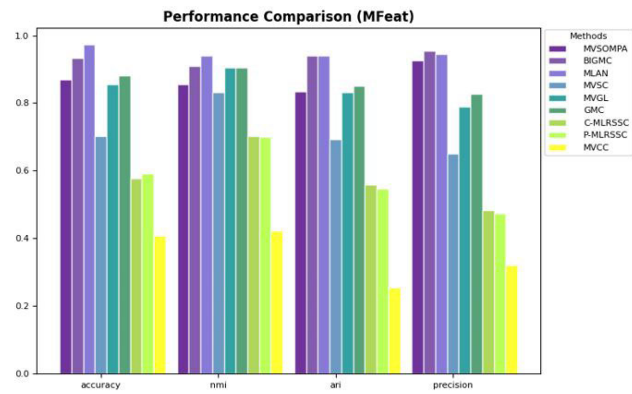

FIGURE 17. Performance comparison with baseline methods (Mean ± Standard deviation) of MFeat dataset.

- The Adjusted Rand Index (ARI)
- The Precision (PRE)
- The Recall (REC)
- The F-Measure (F-M)

The performance metrics for every clustering technique applied to the YaleB dataset are listed in a table. Accuracy (ACC), Precision (PRE), Normalized Mutual Information (NMI), Adjusted Rand Index (ARI), F-Score, and Recall are a few of them. The effectiveness of each approach is displayed as the average number over multiple runs, plus or minus the standard deviation.

The performance metrics for every clustering technique applied to the YaleB, WebKB, Caltech-20, Caltech-7 100Leaves, and 3source datasets are listed in the below tables. Accuracy (ACC), Precision (PRE), Normalized Mutual Information (NMI), Adjusted Rand Index (ARI), F-Score, and Recall are a few of these. The effectiveness of each approach is displayed as the average number over multiple runs, plus or minus the standard deviation.

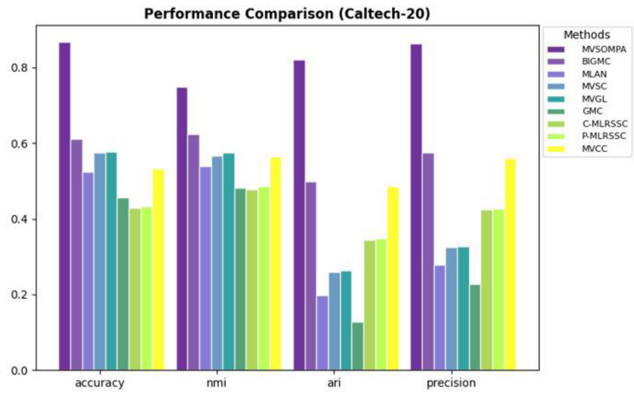

FIGURE 18. Performance comparison with baseline methods (Mean ± Standard deviation) of Caltech-20 dataset.

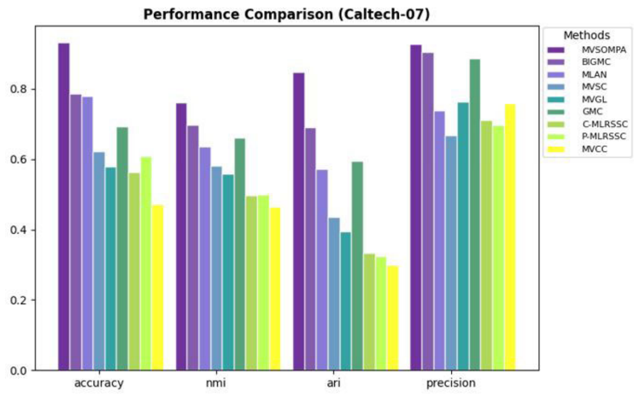

FIGURE 19. Performance comparison with baseline methods (Mean ± Standard deviation) of Caltech-7 dataset.

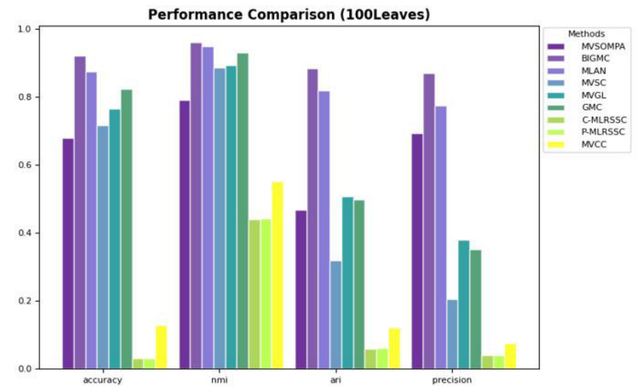

FIGURE 20. Performance comparison with baseline methods (Mean ± Standard deviation) of 100Leaves dataset.

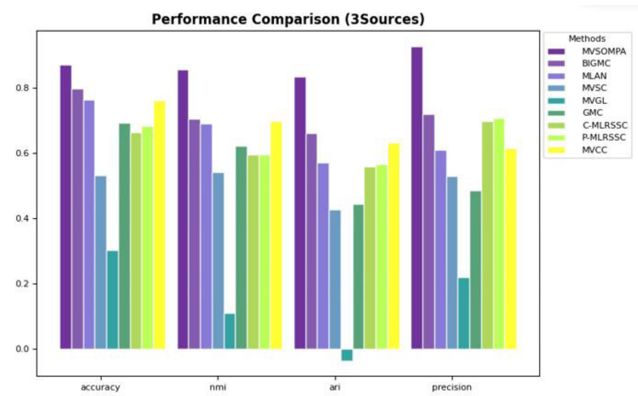

FIGURE 21. Performance comparison with baseline methods (Mean ± Standard deviation) of 3Source dataset.

V. RESULTS

A. RESULTS OF SYNTHETIC DATASETS

Figure 6.1 shows the initial dataset with 200 data points and 0.047 and 0.056 Gaussian noise for View 1 and Vieww 2 respectively.

B. RESULTS OF REAL-TIME-SELF-ORGANIZING DATASET

The method is executed five times, using random nodes for training and testing. The mean and the standard deviations are calculated to analyze the result. Seven real-world datasets are used i.e., Yale B, WebKB, Caltech07, Caltech20, 100 leaves, and three sources.

The results across the seven datasets showcase the performance of the proposed method. In the YaleB dataset, the method achieved an average accuracy of around 61.8%, indicating moderate performance with slight variability across runs. Normalized Mutual Information (NMI) and Adjusted Rand Index (ARI) also demonstrate moderate agreement with the ground truth labels, suggesting a fair clustering performance. Precision, recall, and F-score maintain a balanced performance, reflecting a consistent ability to classify positive and negative instances.

Moving to the WebKB dataset, the proposed method exhibits a higher average accuracy of approximately 78.2% with consistent performance across runs. NMI and ARI metrics indicate moderate agreement with the ground truth labels, while precision, recall, and F-score highlight a robust overall performance, striking a balance between precision and recall.

On the MFEAT dataset, the method achieves a notable average accuracy of 87% with no observed variability across runs. NMI, ARI, precision, recall, and F-score collectively show a strong agreement with the ground truth labels, reflecting consistent and accurate clustering results.

Transitioning to the Caltech101-20 dataset, the method achieves a moderate average accuracy of 78.2%, with some variability observed across runs. While NMI and ARI suggest moderate to strong agreement with the ground truth labels, precision, recall, and F-score maintain moderate levels, indicating a balanced performance in classification.

In contrast, the Caltech101-07 dataset presented a remarkably high average accuracy of 93.6% with no observed variability across runs. Strong agreement with the ground truth labels is indicated by NMI, ARI, precision, recall, and F-score metrics, highlighting consistent and accurate clustering results.

Examining the 100Leaves dataset, the method achieves a moderate average accuracy of 68% with no observed variability across runs. Strong agreement with the ground truth labels is indicated by NMI and ARI, while precision, recall, and F-score maintain moderate levels, suggesting consistent performance in classification.

Lastly, the 3sources dataset demonstrates an excellent average accuracy of 87% with low variability across runs. Strong agreement with the ground truth labels is indicated by NMI, ARI, precision, recall, and F-score metrics, underscoring consistent and accurate clustering results.

In summary, the proposed method displays varying levels of performance across the datasets, with some datasets showcasing higher accuracy and agreement with ground truth labels than others. Overall, the method demonstrates robust and consistent performance across most datasets, with some variability in performance observed across runs and datasets. *

VI. CONCLUSION

The novel proposed architecture has proven its worth in obtaining fine clusters from complex multiview datasets. In this work, many challenges are being faced while developing a worthy method that caters to the multiple views data issues. We achieve the following goals. The Multi Self organizing maps pipeline architecture for Multiview MSOMPA_MV is a much simpler architecture than the iterative joint learning methods. It achieves a significant improvement in performance in multiple Multiview datasets in comparison with other state-of-the-art methods. The Self organizing map topology preserving nature maintains the inner consensus of multiple views. The Self-organizing map plots the high dimensional data to low dimensional space. The novel fusion and clustering technique fuses the information while maintaining the inner and outer consensus. Both the Fusion and clustering stages significantly remove the noisy data. The proposed method shows the success of Multiview learning.

VII. FUTURE WORK

In the future, we are intended to expand the work by applying parameter optimization techniques to ensure good performance. This work can also be extended on incomplete and missing Multiview datasets to cater to the data normalization problem.

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REFERENCES

[1] X. Zhu, S. Zhang, W. He, R. Hu, C. Lei, and P. Zhu, "One-step multi-view spectral clustering," *IEEE Trans. Knowl. Data Eng.*, vol. 31, no. 10, pp. 2022–2034, Oct. 2019, doi: 10.1109/TKDE.2018.2873378.

[2] H. Wang, Y. Yang, B. Liu, and H. Fujita, "A study of graph-based system for multi-view clustering," *Knowl.-Based Syst.*, vol. 163, pp. 1009–1019, Jan. 2019, doi: 10.1016/j.knosys.2018.10.022.

[3] R. Wang, F. Nie, Z. Wang, H. Hu, and X. Li, "Parameter-free weighted multi-view projected clustering with structured graph learning," *IEEE Trans. Knowl. Data Eng.*, vol. 32, no. 10, pp. 2014–2025, Oct. 2020, doi: 10.1109/TKDE.2019.2913377.

[4] Z. Li, C. Tang, X. Liu, X. Zheng, W. Zhang, and E. Zhu, "Consensus graph learning for multi-view clustering," *IEEE Trans. Multimedia*, vol. 24, pp. 2461–2472, 2022, doi: 10.1109/TMM.2021.3081930.

[5] S. Huang, I. W. Tsang, Z. Xu, and J. Lv, "Measuring diversity in graph learning: A unified framework for structured multi-view clustering," *IEEE Trans. Knowl. Data Eng.*, vol. 34, no. 12, pp. 5869–5883, Dec. 2022, doi: 10.1109/TKDE.2021.3068461.

[6] Y. Li, F. Nie, H. Huang, and J. Huang, "Large-scale multi-view spectral clustering via bipartite graph," in *Proc. AAAI Conf. Artif. Intell.*, Feb. 2015, vol. 29, no. 1, pp. 2750–2756.

[7] L. Li and H. He, "Bipartite graph based multi-view clustering," *IEEE Trans. Knowl. Data Eng.*, vol. 34, no. 7, pp. 3111–3125, Jul. 2022, doi: 10.1109/TKDE.2020.3021649.

[8] M. GÃnen and A. A. Margolin, "Localized data fusion for kernel k-means clustering with application to cancer biology," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 27, 2014, pp. 1–9.

[9] L. Du, P. Zhou, L. Shi, H. Wang, M. Fan, W. Wang, and Y.-D. Shen, "Robust multiple kernel k-means using l21-norm," in *Proc. 24th Int. Joint Conf. Artif. Intell.*, 2015.

[10] G. Tzortzis and A. Likas, "Kernel-based weighted multi-view clustering," in *Proc. IEEE 12th Int. Conf. Data Mining*, Dec. 2012, pp. 675–684, doi: 10.1109/ICDM.2012.43.

[11] S. Zhou, X. Liu, M. Li, E. Zhu, L. Liu, C. Zhang, and J. Yin, "Multiple kernel clustering with neighbor-kernel subspace segmentation," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 31, no. 4, pp. 1351–1362, Apr. 2020, doi: 10.1109/TNNLS.2019.2919900.

[12] X. Liu, Y. Dou, J. Yin, L. Wang, and E. Zhu, "Multiple kernel-means clustering with matrix-induced regularization," in *Proc. AAAI Conf. Artif. Intell.*, Feb. 2016, vol. 30, no. 1, doi: 10.1609/aaai.v30i1.10249.

[13] M. Brbić and I. Kopriva, "Multi-view low-rank sparse subspace clustering," *Pattern Recognit.*, vol. 73, pp. 247–258, Jan. 2018, doi: 10.1016/j.patcog.2017.08.024.

[14] C. Zhang, Q. Hu, H. Fu, P. Zhu, and X. Cao, "Latent multi-view subspace clustering," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jul. 2017, pp. 4333–4341, doi: 10.1109/CVPR.2017.461.

[15] R. Li, C. Zhang, Q. Hu, P. Zhu, and Z. Wang, "Flexible multi-view representation learning for subspace clustering," in *Proc. 28th Int. Joint Conf. Artif. Intell.*, Aug. 2019, pp. 2916–2922, doi: 10.24963/ijcai.2019/404.

[16] P. Zhang, X. Liu, J. Xiong, S. Zhou, W. Zhao, E. Zhu, and Z. Cai, "Consensus one-step multi-view subspace clustering," *IEEE Trans. Knowl. Data Eng.*, vol. 34, no. 10, pp. 4676–4689, Oct. 2022, doi: 10.1109/TKDE.2020.3045770.

[17] R. Li, C. Zhang, H. Fu, X. Peng, J. T. Zhou, and Q. Hu, "Reciprocal multi-layer subspace learning for multi-view clustering," in *Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV)*, Oct. 2019, pp. 8171–8179, doi: 10.1109/ICCV.2019.00826.

[18] A. F. R. Araújo, V. O. Antonino, and K. L. Ponce-Guevara, "Self-organizing subspace clustering for high-dimensional and multi-view data," *Neural Netw.*, vol. 130, pp. 253–268, Oct. 2020, doi: 10.1016/j.neunet.2020.06.022.

[19] H. F. Bassani and A. F. R. Araujo, "Dimension selective self-organizing maps with time-varying structure for subspace and projected clustering," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 26, no. 3, pp. 458–471, Mar. 2015, doi: 10.1109/TNNLS.2014.2315571.

[20] Z. Yang, Q. Xu, W. Zhang, X. Cao, and Q. Huang, "Split multiplicative multi-view subspace clustering," *IEEE Trans. Image Process.*, vol. 28, no. 10, pp. 5147–5160, Oct. 2019, doi: 10.1109/TIP.2019.2913096.

[21] P. Zhu, B. Hui, C. Zhang, D. Du, L. Wen, and Q. Hu, "Multi-view deep subspace clustering networks," 2019, *arXiv:1908.01978*.

[22] C. Zhang, S. Wang, J. Liu, S. Zhou, P. Zhang, X. Liu, E. Zhu, and C. Zhang, "Multi-view clustering via deep matrix factorization and partition alignment," in *Proc. 29th ACM Int. Conf. Multimedia*, Oct. 2021, pp. 4156–4164.

[23] M. Ali, T. Mazhar, A. Al-Rasheed, T. Shahzad, Y. Y. Ghadi, and M. A. Khan, "Enhancing software defect prediction: A framework with improved feature selection and ensemble machine learning," *PeerJ Comput. Sci.*, vol. 10, Feb. 2024, Art. no. e1860.

[24] M. Ali, T. Mazhar, Y. Arif, S. Al-Otaibi, Y. Y. Ghadi, T. Shahzad, M. A. Khan, and H. Hamam, "Software defect prediction using an intelligent ensemble-based model," *IEEE Access*, vol. 12, pp. 20376–20395, 2024.

[25] Y. Xie, B. Lin, Y. Qu, C. Li, W. Zhang, L. Ma, Y. Wen, and D. Tao, "Joint deep multi-view learning for image clustering," *IEEE Trans. Knowl. Data Eng.*, vol. 33, no. 11, pp. 3594–3606, Nov. 2021, doi: 10.1109/TKDE.2020.2973981.

[26] Z. Li, Q. Wang, Z. Tao, Q. Gao, and Z. Yang, "Deep adversarial multi-view clustering network," in *Proc. 28th Int. Joint Conf. Artif. Intell.*, Aug. 2019, pp. 2952–2958, doi: 10.24963/ijcai.2019/409.

[27] X. Peng, Z. Huang, J. Lv, H. Zhu, and J. T. Zhou, "COMIC: Multi-view clustering without parameter selection," in *Proc. Int. Conf. Mach. Learn.*, 2019, pp. 5092–5101.

[28] C. Zhang, Y. Geng, Z. Han, Y. Liu, H. Fu, and Q. Hu, "Autoencoder in autoencoder networks," *IEEE Trans. Neural Netw. Learn. Syst.*, pp. 1–13, 2022, doi: 10.1109/TNNLS.2022.3189239.

[29] (2023). *Caltech 101*. Accessed: Feb. 14, 2023. [Online]. Available: https://data.caltech.edu/records/mzrjq-6wc02

[30] (2023). *UCI Machine Learning Repository: Multiple Features Data Set*. Accessed: Feb. 14, 2023. [Online]. Available: https://archive.ics.uci.edu/ml/datasets/Multiple

[31] (2023). *Yale Face Database B | Computer Vision Online*. Accessed: Feb. 14, 2023. [Online]. Available: https://computervisiononline.com/dataset/1105138686

[32] (2023). *WebKB StARLinG*. Accessed: Feb. 14, 2023. [Online]. Available: https://starling.utdallas.edu/datasets/webkb/

[33] (2023). *UCI Machine Learning Repository: One-Hundred Plant Species Leaves Data Set Data Set*. Accessed: Feb. 14, 2023. [Online]. Available: https://archive.ics.uci.edu/ml/datasets/One-hundred+plant+species+leaves+data+set

[34] (2023). *ML Resources 3 Sources Dataset*. Accessed: Feb. 14, 2023. [Online]. Available: http://mlg.ucd.ie/datasets/3sources.html

[35] F. Nie, G. Cai, and X. Li, "Multi-view clustering and semi-supervised classification with adaptive neighbours," in *Proc. AAAI Conf. Artif. Intell.*, Feb. 2017, vol. 31, no. 1, doi: 10.1609/aaai.v31i1.10909.

[36] H. Wang, Y. Yang, and T. Li, "Multi-view clustering via concept factorization with local manifold regularization," in *Proc. IEEE 16th Int. Conf. Data Mining (ICDM)*, Dec. 2016, pp. 1245–1250, doi: 10.1109/ICDM.2016.0167.

[37] A. Ultsch, "Self-organizing neural networks for visualisation and classification," in *Proc. Inf. Classification, Concepts, Methods Appl., Proc. 16th Annu. Conf. Gesellschaft füür Klassifikation eV Univ. Dortmund*. Berlin, Germany: Springer, Apr. 1993, pp. 307–313.

[38] L. Li, Z. Wan, and H. He, "Incomplete multi-view clustering with joint partition and graph learning," *IEEE Trans. Knowl. Data Eng.*, vol. 35, no. 1, pp. 589–602, Jan. 2023, doi: 10.1109/TKDE.2021.3082470.

[39] H. Ishibashi and T. Furukawa, "Self-organizing maps for multi-system and multi-view datasets," in *Proc. Joint 8th Int. Conf. Soft Comput. Intell. Syst. (SCIS) 17th Int. Symp. Adv. Intell. Syst. (ISIS)*, Aug. 2016, pp. 343–348, doi: 10.1109/SCIS-ISIS.2016.0078.

[40] W. Wan and D. Fraser, "Multisource data fusion with multiple self-organizing maps," *IEEE Trans. Geosci. Remote Sens.*, vol. 37, no. 3, pp. 1344–1349, May 1999, doi: 10.1109/36.763298.

[41] W. Wan and D. Fraser, "A multiple self-organizing map scheme for remote sensing classification," in *Proc. Int. Workshop Multiple Classifier Syst.*, 2000, pp. 300–309, doi: 10.1007/3-540-45014-9_29.

[42] P. Fränti and S. Sieranoja, "How much can k-means be improved by using better initialization and repeats?" *Pattern Recognit.*, vol. 93, pp. 95–112, Sep. 2019, doi: 10.1016/j.patcog.2019.04.014.

[43] M. L. Goncalves, M. L. de Andrade Netto, J. A. F. Costa, and J. Zullo, "Data clustering using self-organizing maps segmented by mathematic morphology and simplified cluster validity indexes: An application in remotely sensed images," in *Proc. IEEE Int. Joint Conf. Neural Netw.*, Jul. 2006, pp. 4421–4428, doi: 10.1109/IJCNN.2006.247043.

[44] R. Zhang, F. Nie, X. Li, and X. Wei, "Feature selection with multi-view data: A survey," *Inf. Fusion*, vol. 50, pp. 158–167, Oct. 2019, doi: 10.1016/j.inffus.2018.11.019.

[45] S. Manochandar, M. Punniyamoorthy, and R. K. Jeyachitra, "Development of new seed with modified validity measures for k-means clustering," *Comput. Ind. Eng.*, vol. 141, Mar. 2020, Art. no. 106290, doi: 10.1016/j.cie.2020.106290.

[46] A. José-García and W. Gómez-Flores, "A survey of cluster validity indices for automatic data clustering using differential evolution," in *Proc. Genetic Evol. Comput. Conf.*, Jun. 2021, Art. no. 314322, doi: 10.1145/3449639.3459341.

[47] S. Wu and T. W. S. Chow, "Clustering of the self-organizing map using a clustering validity index based on inter-cluster and intra-cluster density," *Pattern Recognit.*, vol. 37, no. 2, pp. 175–188, Feb. 2004, doi: 10.1016/s0031-3203(03)00237-1.

[48] S. Sieranoja and P. Fränti, "Adapting k-means for graph clustering," *Knowl. Inf. Syst.*, vol. 64, no. 1, pp. 115–142, Jan. 2022, doi: 10.1007/s10115-021-01623-y.

[49] S. F. Hussain and M. Haris, "A k-means based co-clustering (kCC) algorithm for sparse, high dimensional data," *Expert Syst. Appl.*, vol. 118, pp. 20–34, Mar. 2019, doi: 10.1016/j.eswa.2018.09.006.

[50] N. Ziraki, F. Dornaika, and A. Bosaghzadeh, "Multiple-view flexible semi-supervised classification through consistent graph construction and label propagation," *Neural Netw.*, vol. 146, pp. 174–180, Feb. 2022, doi: 10.1016/j.neunet.2021.11.015.

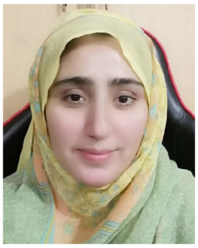
[51] G. A. Khan, J. Hu, T. Li, B. Diallo, and H. Wang, "Multi-view data clustering via non-negative matrix factorization with manifold regularization," *Int. J. Mach. Learn. Cybern.*, vol. 13, no. 3, pp. 677–689, Mar. 2022, doi: 10.1007/s13042-021-01307-7.

[52] M.-S. Yang and K. P. Sinaga, "A feature-reduction multi-view k-means clustering algorithm," *IEEE Access*, vol. 7, pp. 114472–114486, 2019, doi: 10.1109/ACCESS.2019.2934179.

[53] V. O. Antonino and A. F. R. Araujo, "Local adaptive receptive field dimension selective self-organizing map for multi-view clustering," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Jul. 2016, pp. 698–705, doi: 10.1109/IJCNN.2016.7727268.

[54] A. Filippi, I. Dobreva, A. G., and J. R., "Self-organizing map-based applications in remote sensing," in *Self-Organizing Maps*. Rijeka, Croatia: InTech, 2010, doi: 10.5772/9163.

[55] C. Saavedra, R. Salas, S. Moreno, and H. Allende, "Fusion of self organizing maps," in *Computational and Ambient Intelligence*. Berlin, Germany: Springer, 2007, pp. 227–234, doi: 10.1007/978-3-540-73007-1_28.



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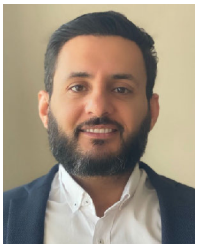

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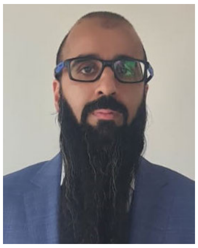

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