Global Journal of Computer Science and Technology: C
Software & Data Engineering
Volume 16 Issue 3 Version 1.0 Year 2016
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals Inc. (USA)
Online ISSN: 0975-4172 & Print ISSN: 0975-4350

5M: Multi-Instance Multi-Cluster based Weakly Supervised MIL Model for Multimedia Data Mining

By Girisha GS & Dr. K. Udaya Kuma

BNM Institute of Technology

Abstract- The high pace rise in online as well as offline multimedia un annotated data and associated mining applications have demanded certain efficient mining algorithm. Multiple instance learning (MIL) has emerged as one of the most effective solutions for huge un annotated data mining. Still, it requires enhancement in instance selection to enable optimal mining and classification of huge multimedia data. Considering critical multimedia mining applications, such as medical data processing or content based information retrieval, the instance verification can be of great significance to optimize MIL. With this motivation, in this paper, Multi-Instance, Multi-Cluster based MIL scheme (MIMC-MIL) has been proposed to perform efficient multimedia data mining and classification with huge un annotated data with different features. The proposed system employs soft max approximation techniques with a novel loss factor and inter-instance distance based weight estimation scheme for instance probability substantiation in bags.

Keywords: multimedia data mining, multiple instance learning, multi-instance, multi -cluster based mining.

GJCST-C Classification : H.2.4 H.2.8

5MMULTIINSTANCEMULTICLUSTERBASEDWEAKLYSUPERVISEDMILMODELFORMULTIMEDIADATAMINING

Strictly as per the compliance and regulations of:

5M: Multi-Instance Multi-Cluster based Weakly Supervised MIL Model for Multimedia Data Mining

Girisha GS [α] & Dr. K. Udaya Kumar [σ]

Abstract- The high pace rise in online as well as offline multimedia un annotated data and associated mining applications have demanded certain efficient mining algorithm. Multiple instance learning (MIL) has emerged as one of the most effective solutions for huge un annotated data mining. Still, it requires enhancement in instance selection to enable optimal mining and classification of huge multimedia data. Considering critical multimedia mining applications, such as medical data processing or content based information retrieval, the instance verification can be of great significance to optimize MIL. With this motivation, in this paper, Multi-Instance, Multi-Cluster based MIL scheme (MIMC-MIL) has been proposed to perform efficient multimedia data mining and classification with huge un annotated data with different features. The proposed system employs soft max approximation techniques with a novel loss factor and inter-instance distance based weight estimation scheme for instance probability substantiation in bags. Unlike conventional clustering scheme, the proposed MIMC algorithm performs instance-level verification, class-level clustering and bag-level classification, simultaneously to perform mining with minimal possible complexity. The performance evaluation with SIVAL image datasets with 10 fold cross validation affirms that the proposed system performs better than existing clustering based approaches.

Keywords: multimedia data mining, multiple instance learning, multi-instance, multi-cluster based mining.

I. Introduction

The high pace emergence of information technologies and associated applications, the accumulation of data and its efficient mining and information retrieval has been increasing with a exponentially. Recently, Multimedia Data mining has emerged as one of the most sought technology. MDM can be stated as the process dealing with data processing based intended multimedia data or information retrieval. Multimedia data can be of various categories such as video, audio, image, animation, moving data sequences, etc. MDM exhibits various tasks such as prediction, or trend analysis based on association retrieval, clustering, and classification etc.

Author α: Research Scholar, Department of Information Science & Engineering, BNM Institute of Technology, Bangalore, India.
e-mail: girisha_gs@yahoo.com,
Author σ: Principal, Adarsha Institute of Technology, Bengaluru, Karnataka, India. e-mail: udayakumarkrishnappa@gmail.com

The rising applications and utilities have motivated academia-industries to develop certain optimal technique for MDM.

Numerous approaches such as machine learning, artificial neural network, and association rule mining etc have been used for MDM. However; most of the existing approaches do fail to process large scale data sets. Moreover, it gets more complicate with the huge un annotated data. The emergence of MIL [1] has enabled better learning and classification efficiency than conventional supervised learning schemes. With the motivation to develop a robust and efficient MDM technique, in this paper an efficient MIL algorithm has been developed to classify un annotated multimedia data. In function, MIL classifies bags of instances, where bags represent the images and instances signify related features. In MIL, the labelling is performed on each bag and hence instance based labelling is not required. Such features significantly reduce the computational complexity and makes classification efficient.

MIL approach have exhibited appreciable effectiveness for major applications such as mining application, Classification [2], Vision based biomedical applications and His to pathological data analysis [1], Content Based Image Retrieval (CBIR) [3], Moving object detection [4], Image and Video processing [5][6], and numerous surveillance applications [7,8]. A number of MIL algorithms have been proposed such as APR [1], DD [9], EM-DD [10] that used a generative models to identify the concept region or the region of interest (ROI) by localizing all the true positive instances in the region space or feature space. In such schemes, the Single-Instance Learning (SIL) problems are generalized to the MIL problem. To achieve better performance recently few efforts were made that intend to explore the additional machine learning approach for classification. Some of these MIL algorithms are MI-SVM [2], MI-Kernel [11], MIO [12], Citation KNN [13] and MIL Boost-NOR [14]. Furthermore, MIL schemes such as DD-SVM [5], MILES [4], MILD B [15] and MILIS [16] have also used support vector machine (SVM) to perform classification. Considering significance of clustering scheme for MIL algorithm, in [17] a Multiple Instance Clustering Scheme was developed that primarily functions to learn the clusters formed by similar instances. However, this

Global Journal of Computer Science and Technology (C) Volume XVI Issue III Version I Year 2016

approach could consider only one cluster to perform classification and does not consider any negative bag during classification. In [18] multiple components were assessed to detect single object class. On contrary, in this paper we have developed multi-instance, multi-cluster based MIL model (MIMC-MIL) for MDM. In the proposed model, we have considered multiple instances in one cluster and multiple clusters in bag for effective classification accuracy. In [19, 20], few assumptions were incorporated to form multiple label MIL to perform multimedia data (image) classification. Our proposed MIMC-MIL model employs soft max approximation to estimate the probability of an instance in a bag to perform multimedia mining. The enhanced loss function and fair weight estimation based MIMC-MIL scheme has exhibited better performance than other existing systems. The remaining sections of the paper are presented as; Section II discusses the proposed MIMC-MIL algorithm and its implementation for ROI verification, clustering and classification. Section III presents results and analysis, which is then followed by conclusion in Section IV. References used in this paper are given at the last.

II. Our Contribution

In this paper, the general concept of bag and instance based weekly supervised MIL algorithm has been considered for multimedia mining. The generic functional definition of MIL states that even if a bag contains at least one positive instance, it can be labelled as positive bag. On contrary, the rise in highly critical data mining where accuracy plays significant role, such as medical data analysis and vision based decision process, such hypothesis often creates suspicion and question over functional accuracy and reliability. There are a number of multimedia mining applications where classification accuracy is of great significance and therefore to alleviate such ambiguity in conventional MIL approaches, the verification of the Region of Interest (ROI) also called concept region in bags can be vital. With this intention, in our previous work [25], we developed a single level clustering based ROI instance verification algorithm for multimedia data mining (MDM) and classification. In [25], the classification was done on cluster level. However, realizing the requirement of more precise and accurate mining performance, instance level analysis can be of great significance. The multiple instance based ROI verification and respective class formation (clustering in individual bag), followed by the multi-level clustering can ensure more effective and accurate mining performance. With this motivation, in this paper a highly robust and efficient Multi-Instance, Multi-Clustering based weakly supervised MIL learning model (MIMC-MIL) has been developed for MDM applications. Generally, a typical clustering based MDM encompasses three phases; segmentation, clustering and classification. These all process introduces huge computational complexity and computation time if executed individually to perform MDM. In case of huge un annotated data; such limitations turn out to be more severe. Hence, to alleviate such limitations, the proposed MIMC-MIL model performs these three processes simultaneously. The proposed mining model performs instance or pixel level segmentation, patch level clustering and bag label (image label) classification simultaneously that enables optimal mining performance for huge un annotated data. Unlike conventional Machine Learning and artificial Neural Network (ANN) algorithm, MIMC-MIL can perform segmentation and classification of multimedia data simultaneously to ensure optimal mining efficiency. The overall proposed model of MIMC based multimedia mining and classification is given in Fig. 1.

In this paper, numerous novelties such as an enhanced loss factor and weight estimation model based soft max approximation techniques has been developed which ensure optimal ROI probability estimation in bags and hence enable more efficient mining and classification accuracy. Here we have considered an assumption that based on certain ROI or concept region, the segmentation and classification can be done using MIL approach. The same concept has been used in our MIMC-MIL based MDM model. As depicted in Fig. 1, the multimedia data SIVAL with 180 positive and equally negative bags have been considered to evaluate the mining and classification efficiency. In this paper, the feature extracted values for the images are taken as input, which is then followed by clustering and ROI verification by our proposed MIMC-MIL model.

a) Multi-Instance, Multi-Cluster Based stance Verifi -cation Model for Multiple Instance Learning

Using multimedia benchmark data as, the MIL approach selects set of features as training data, which is also known as a bag. Mathematically bag can be defined as $\mathcal{X}_i = \{\mathcal{X}_{i1}, \ldots, \mathcal{X}_{im}\}$ and for k cluster, the individual bag is associated with a label, which can be defined as $y_{ij}^{k} \in \mathcal{Y} = \{-1, 1\}$. In other words, the individual instance $(x_{ij} \in \mathcal{X})$ in a bag $(\mathcal{X}_{ij} \in \mathcal{X}^m)$ possesses a true label $(y_{ij}^{k} \in \mathcal{Y})$ as a hidden variable that remains unknown during feature mining and training for further classification.

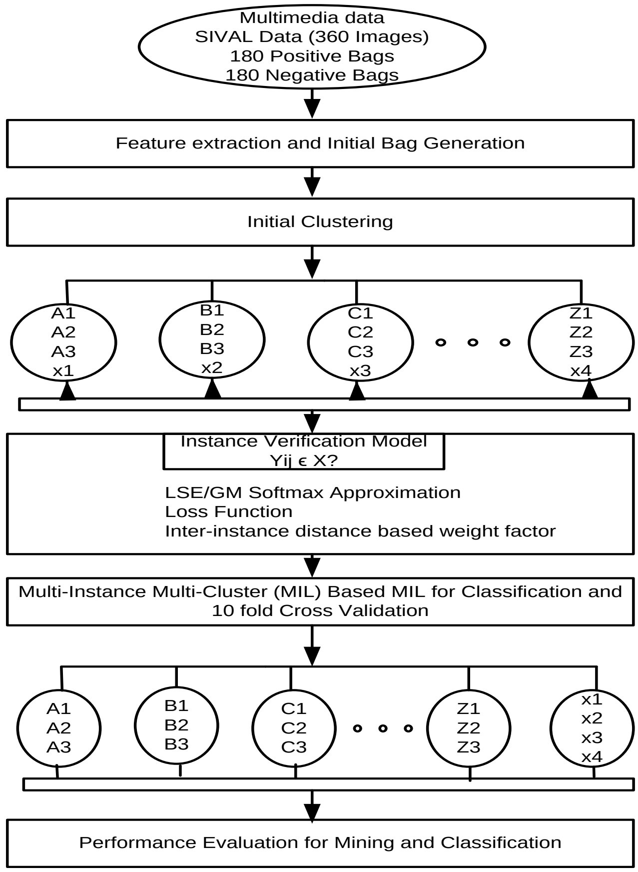

Fig.1 : Proposed MIMC based MIL model for Multimedia data mining

A bag is labelled as positive when x_{ij}belongs to the k^{th} cluster, i.e.$y_{ij}^{k} = 1$. As already stated, a bag can be labelled as positive if minimum one instance is positive and belongs to the k^{th}cluster. Mathematically,

$$y_i = \max_j \left(y_{ij}^{k} \right) \qquad (1)$$

where max is similar to an OR operator because $y_{ij}^{k} \in \mathcal{Y}, max_j \left(y_{ij}^{k} \right) = 1 \Longleftrightarrow \exists_j$, provided$y_{ij} = 1$.

In general, the predominant objective of an MIL algorithm is to perform learning at instance-level classifier $h(x_{ij}) : \mathcal{X} \rightarrow \mathcal{Y}$. MIL intends to provide an efficient learning mode for splitting the positive instances into $\mathcal{K}$ clusters by means of $\mathcal{K}$ instance level classifiers$h(x_{ij}) : \mathcal{X} \rightarrow \mathcal{Y}$. In this process, the labelled bags y_i are used in such a manner that $max_j \max_k h(x_{ij}) = y_i$. Unlike conventional MIL approaches [21, 22, 23], we have introduced a loss function to estimate the optimal weak classifier response $h_t^{k}: \mathcal{X} \rightarrow \mathcal{Y}$ that significantly reduces the loss on training data. Mathematically, the loss function is given by:

$$\mathcal{L}_{\mathcal{A}}(h) = -\sum_{i=1}^{n} w_i \left(1(y_i = 1) log p_i + \right.$$
$1 y j = -1 log 1 - p i$, and

$$\mathcal{L}_{\mathcal{B}}(h) = \sum_{i=1}^{n} w_i \sum_{(j,m) \in \mathcal{E}_i} v_{jm} \left\| p_{ij} - p_{im} \right\|^2 \qquad (2)$$

where w_i represents the initial weight of the i^{th} training data and $1(\cdot)$ states certain index function. The variable $\mathcal{E}_i$represents the group of the pairs of all the neighbouring instances in i^{th}bag or training data. Here, v_{jm}represents the weight on the patches, which is nothing else but the pair of instances (features). The variables d_{jm} represents the relative distance between j and m. If the instances are closer, then they are assigned with higher weights. To estimate the respective weights $\left(v_{jm} \right)$ of the instances and patches, we have used$v_{jm} = exp\left(-d_{jm} \right)$. Thus, estimating the value of v_{jm}, the cumulative loss function (CLF) (2) has been estimated using equation (3).

$$CLF = \mathcal{L}(h) = \mathcal{L}_{\mathcal{A}}(h) + \lambda \mathcal{L}_{\mathcal{B}}(h) \qquad (3)$$

Here, $\mathcal{L}_{\mathcal{B}}(h)$ plays significant role to eliminate the ambiguity during training by imposing an efficient contextual constraint over the instances and thus enabling neighbouring images (patches formed by instances) to share analogous classes. The other loss function, $\mathcal{L}_{\mathcal{A}}(h)$ states the typical negative log likelihood. Variable λ represents the weight associated with the supplementary item that signifies the importance of the inter-relationship between the neighbouring instances (instance represents unit features of the image). Thus, the proposed mining and

Global Journal of Computer Science and Technology (C) Volume XVI Issue III Version I Year 2016

classification system can be considered as resilient of noise as well as robust for effective segmentation purposes. In our proposed model, the training of h_t^k has been performed by reducing error associated with the training data, which is estimated by weight factor w_{ij}^k

$$\left| w_{ij}^k \right| : h_t^k = \arg\min_{h} \sum_{i,j} \left(h(w_{ij}^k) \neq y_i{}^k \right) \left| w_{ij}^k \right| \tag{4}$$

where, $w_{ij}^k \equiv -\frac{\partial \mathcal{L}(h)}{\partial h_{ij}^k}$.

Here, a soft max function $g_\ell(v)$ has been considered that performs approximations of max value over $v = \{v_1, .., v_m\}$. There are a number of approximation approaches, such as noisy-OR (NOR), generalized mean (GM), log-sum-exponential (LSE), and integrated segmentation and recognition (ISR). Unlike our previous work [25], where NOR model was used, in this paper we have applied GM and LSE approximation techniques individually to perform approximation over $v = \{v_1, .., v_m\}$. In addition, a factor named sharpness control factor (SCF), r has been introduced to enhance the classification efficiency by means of controlling the sharpness during approximation for instance probability estimation. The mathematical presentation of the soft max approximation of GM and LSE models are given in Table I.

Table 1 : Soft max approximation models

Model	$g_\ell(v_\ell)$	$\frac{\partial g_\ell(v_\ell)}{\partial v_i}$	Domain
GM	$\left(\frac{1}{m}\sum_l v_\ell^r\right)^{\frac{1}{r}}$	$g_\ell(v) = \frac{v_i^{r-1}}{\sum_\ell v_\ell^r}$	[0, ∞]
LSE	$\frac{1}{r} ln \frac{1}{m} \sum_{exp} (r v_\ell)$	$\frac{\exp(r v_i)}{\sum_\ell \exp(r)}$	[-∞,∞]

Since $r \to \infty$, soft max approximations can be observed as $g_\ell(v) \approx max_\ell(v)\, g_\ell(v) \to v^*$. Thus, for m variables($v = \{v_1, \dots, v_m\}$), the respective softmax function $g_\ell(v)$ can be obtained by

$$g_\ell(v) \approx \max_\ell (v_\ell) = v, \frac{\partial g_\ell(v)}{\partial v_i} \approx \frac{1(v_i = v^*)}{\sum_l 1\,(v_i = v^*)} \tag{5}$$

where, $m = |v|$. To maintain simplified presentation, in rest of the paper, the variable $g_\ell(v)$ has been represented by g, while v_ℓ is represented in terms of ℓ. In order to enhance the loss function $\mathcal{L}$, at first the probability p_i of bag is required to be estimated, which is stated to be the highest over p_{ij}^k. Here, the probability that an instance x_{ij} belongs to the k^{th} cluster, is given by

$$p_{ij}^k = \sigma(2h_{ij}^k) \tag{6}$$

where $h_{ij}^k = h^k(x_{ij})$.

Now, substituting max with g, the instance probability p_i in a class can be obtained as

$$p_i = g_j\left(g_k(p_{ij}^k)\right) = g_{jk}(p_{ij}^k) = g_{jk}\left(\sigma(2h_{ij}^k)\right) \tag{7}$$

where

$$\sigma(v) = \frac{1}{1 + \exp(-v)}$$

The optimal weighted error factor (w_{ij}) and the derivative $\frac{\partial \mathcal{L}}{\partial h_{ij}^k}$ can be obtained as

$$w_{ij}^k = \frac{\partial \mathcal{L}(h)}{\partial h_{ij}^k} = -\frac{\partial \mathcal{L}(h)}{\partial p_i}\frac{\partial p_i}{\partial p_{ij}^k}\frac{\partial p_{ij}^k}{\partial h_{ij}^k}. \tag{8}$$

Thus, performing the optimization of weighed error factor $\left|w_{ij}^k\right|$, the weak classifier h_{ij}^k has been trained efficiently. Finally, a string classifier has been obtained as

$$h^k \leftarrow h^k + \alpha_t^k\, h_t^k \tag{9}$$

where α_t assess weighing of the relative significance of the weak learner. Thus, implementing our proposed MIMC-MIL, the instance verification in each bag can be done and respective accurate clustering based classification can be performed.

b) *Mimc-Mil Based Multimedia Mining*

Multimedia data can be of different types and in huge quantity. The conventional systems suffer from extraction or classification, particularly with huge un annotated data. In addition to the annotation issues, unclear type and nature of multimedia data requires efficient approaches for mining. In a number of MDM systems, clustering has been used for mining and classification. The existing cluster based approaches do apply single level of clustering to perform classification, but considering critical applications, where the misplacement of a single instance or feature can alter the prediction and further decision process, the conventional clustering based mining schemes requires multilevel instance verification. In other words, the probability estimation of an instance of multimedia data in certain class can enable better clustering accuracy and hence can enable enhanced mining classification. In this paper, the MIMC based MIL scheme has been applied for mining and classification, where each instance and its probability of belongingness to certain class or cluster has been done. In general, most of the existing MDM techniques use three different approaches; segmentation, clustering, and classification. The execution of these all approaches with the huge data, turns out to be highly complicate and time consuming. Therefore, to deal with such limitation, we have used the proposed MIMC-MIL scheme that performs clustering, segmentation and classification simultaneously.

Global Journal of Computer Science and Technology (C) Volume XVI Issue III Version I Year 2016

In this paper, to perform multimedia mining and classification a benchmark multimedia data containing huge images with different features has been considered from which the training data ($\mathcal{X}_i = \mathcal{X}i1, \ldots, \mathcal{X}im$ has been prepared and respective labelling of bags ($y_i \in \mathcal{Y} = \{-1,1\}$) has been done. Performing the initial clustering and bag formation from benchmark data the proposed MIMC algorithm has been applied as presented in Fig. 1. Table II represents the training data (input) and learning objective definition.

Table 2 : Training data and its objective formulations

TECHNIQUE	TRAINING DATA	OBJECTIVE
		$x_i \rightarrow Classification$ $x_{ij} \rightarrow Segmentation$ $y_{ij}^{k} \rightarrow Clustering$
Standard Classifier	x_i	$x_i \rightarrow \{-1,1\}$
Conventional MIL	$x_i = \{x_{i1}, \ldots, x_{im}\}$ $x_{ij} \in x$	$x_i \rightarrow \{-1,1\}$; $x_{ij} \rightarrow \{-1,1\}$
Proposed MIL	$x_i = \{x_{i1}, \ldots, x_{im}\}$ $x_{ij} \in x$	$x_i \rightarrow \{-1,1\}$; $x_{ij} \rightarrow \{-1,1\}$ $y_{ij}^{k} \rightarrow \{y_{ij}^{1}, \ldots, y_{ij}^{k}\}$;

Table II depicts that the proposed MIMC-MIL scheme is capable of performing patch level clustering($x_{ij} \rightarrow \{y_{ij}^{1}, \ldots, y_{ij}^{k}\}$; $y_{ij}^{k} \in \{-1,1\}$), segmentation($x_{ij} \rightarrow \{-1,1\}$) at pixel-level, and classification at bag or image level($x_i \rightarrow \{-1,1\}$). To perform MDM at first feature vectors have been prepared from benchmark data which has been fed as the input of MIMC-MIL algorithm where the learning for multilevel ($\mathcal{K}$ instance-level) classification has been done $h^{k}(x_{ij}): \mathcal{X} \rightarrow \mathcal{Y}$ for $\mathcal{K}$clusters. Consequently, the bag-level classifier for certain k^{th} cluster has been formed as$h^{k}(x_i): \mathcal{X}^m \rightarrow \mathcal{Y}$. Thus, the overall classification approach for MDM can be stated as$\mathcal{H}(x_i): \mathcal{X}^m \rightarrow \mathcal{Y}$.

$$\mathcal{H}(x_i) = \max_{k} h^{k}(x_i) \max_{k} \max_{j} h^{k}(x_{ij}) \tag{10}$$

As an optimization of our previous work [25], in this paper the ROI probability factor p_i has been estimated in terms of the softmax of $p_{ij} \equiv p(y_{ij} = 1|y_{ij})$ for all the associated instances in the bags (image dataset). ROI instance probability (p_{ij}) in a bag (bag represents the image having multiple clusters, where clusters are formed by instances) has been estimated $\left(p_{ij}^{k} = p(y_{ij}^{k} = 1|x_{ij})\right)$ using LSE and GM based soft max approximation technique. The eventual instance probability is obtained as:

$$p_i = g_j(p_{ij}) = g_j(g_k(p_{ij}^{k})) \tag{11}$$

where p_{ij}^{k} represents the probability that the ROI or the concept region instance x_{ij} belongs to the k^{th} cluster.

The overall MIMC-MIL based mining and classification model is given in Fig. 1.

Input: Multimedia data extracted features or Bags $\{\mathcal{X}_1, \ldots, \mathcal{X}_n\}, \{y_1, \ldots, y_n\}, \mathcal{K}$ cluster, $\mathcal{T}$ Threshold
Output: $h^1, \ldots, h^k$
for $t = 1 \rightarrow \mathcal{T}$ do
for $k = 1 \rightarrow \mathcal{K}$ do
Calculate $\mathcal{L}_{\mathcal{A}}(h)$ and $\mathcal{L}_{\mathcal{B}}(h)$
Calculate weights $w_{ij}^{k} = \mathcal{L}(h) = \mathcal{L}_{\mathcal{A}}(h) + \lambda \mathcal{L}_{\mathcal{B}}(h)$

$$-\frac{\partial \mathcal{L}(h)}{\partial h_{ij}^{k}} = -\frac{\partial \mathcal{L}_{\mathcal{A}}(h)}{\partial p_i} \frac{\partial p_i}{\partial p_{ij}^{k}} \frac{\partial p_{ij}^{k}}{\partial h_{ij}^{k}} + \lambda \frac{\partial \mathcal{L}_{\mathcal{B}}(h)}{\partial p_i} \frac{\partial p_{ij}^{k}}{\partial h_{ij}^{k}}$$

Perform training of the weak classifier h_t^{k} using weights w_{ij}^{k}

$$h_t^{k} = arg \min_{h} \sum_{ij} 1\left(h(x_{ij}^{k}) \neq y_i^{k}\right) |w_{ij}^{k}|$$

Calculate α_t by means of the line search so as to reduce CLF $\mathcal{L}(., h^k + \alpha\, h_t^k, .)$
Update strong classifier $h^k \leftarrow h^k + \alpha_t^k\, h_t^k$
Form final cluster with ROI/ verified instances
end for
end for

Fig. 2 : Algorithm for proposed MIMC based mining and classification

A brief of the three significance functional phases of MIMC-MIL is given as follows:

i. *Classification*

In this paper, initially the image level classification has been done that exploits the developed instance verification and clustering approach. Here, the overall features or instances x_{ij} of complete image data have been used to perform training as per [22]. The training approach uses our developed Multi-Instance Multi-Cluster (MIMC) instance features or instance-level labels retrieved from the labels prepared on bag-level ($y_{ij} = y_i$, $i = 1, \ldots, n, j = 1, \ldots, m$) and thus based on the final clustering output the classification has been done.

ii. *Segmentation*

In multimedia mining applications, especially when there are huge data, it becomes too intricate, ambiguous and computationally complex to perform annotations for all the data (image). The proposed MIMC-MIL scheme doesn't demands huge annotation or even any instance-level supervision. The proposed algorithm selects few ROI data, also called concept data randomly along with some other non-ROI data to form a

Global Journal of Computer Science and Technology (C) Volume XVI Issue III Version I Year 2016

training subset. Our proposed algorithm generates probability mapping for all instances (p_i) associated with bag X_i. Thus, implementing MIMC-MIL classifier, the parameters such as accuracy, recall and F-measures have been estimated. F-measure factor $2.\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$ can be used for segmentation.

iii. *Clustering*

As discussed in previous sections, the proposed MIMC-MIL approach performs clustering while performing instance verification or ROI classification for mining. Furthermore, the proposed system performs pixel level segmentation that can be further inter-related with patch level (collection of the instances having similar dimensions and features) clustering. The standard boosting has been applied to perform instance level segmentation, which can then be followed by K-means algorithm to perform clustering of the positive instances (concept region or ROI).

III. Results and Discussion

With an objective to perform multimedia data mining, in this paper a robust and enhanced clustering based multi-instance multi-cluster MIL (MIMC-MIL) scheme has been developed. The overall proposed model has been developed using MATLAB 2014b software tool. To evaluate the performance SIVAL dataset has been used. The considered datasets encompasses 360 bags containing 180 bags each for positive and negative type. The images in SIVAL dataset are presented in Table III. To evaluate the performance of the proposed system, the 10-fold cross validation has been done and performance evaluation has been done in terms of classification accuracy and area under ROC (AUC) curve. As already stated, in the proposed algorithm, two distinct soft max approximation algorithms have been used and hence the proposed algorithm has been evaluated with the both generalized mean (GM) and log-sum-exponential (LSE) algorithm. The results obtained for accuracy and AUC are given in the following figures.

Table 3 : Images in SIVAL dataset

SIVAL IMAGE DATA	
Positive Bag	Negative Bag
Smiley face doll	Checker edscarf
Blues crunge	Dirty running shoe
Green tea box	Felt flower rug

In this paper the multimedia data mining and classification has been performed with ROI verification and clustering by means of GM and LSE soft max approximation techniques individually. Fig. 3 and Fig. 4 represent the mining and classification accuracy using proposed MICL-MIL algorithm with log-sum-exponential (LSE) and generalized model (GA) soft max approximation techniques respectively. Here, it can be observed that LSE model performs better with our proposed MIMC algorithm. Interestingly, LSE model with our proposed MIMC algorithm performs better than with conventional boosting based MIL scheme.

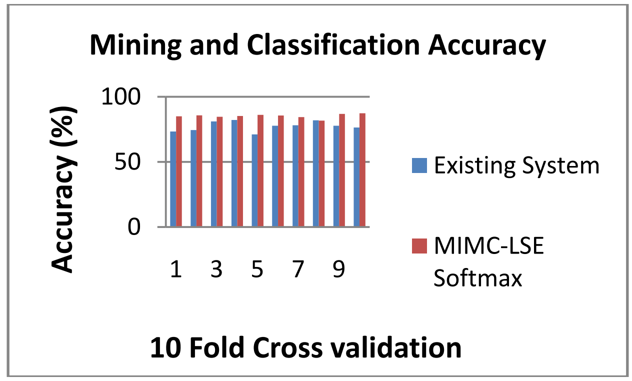

Fig. 3 : Mining and classification accuracy using LSE Soft max approximation

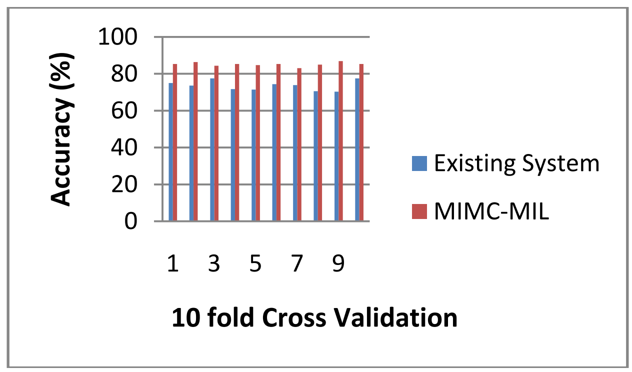

Fig. 4 : Mining and classification accuracy using GM Soft max approximation

Fig. 5 and Fig. 6 affirms that LSE soft max performs better with the proposed MIMC based MIL for multimedia data mining.

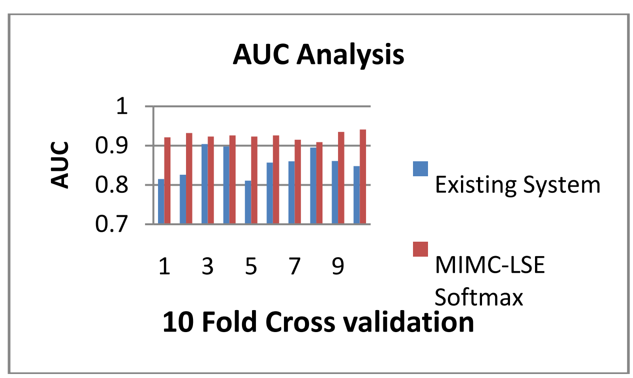

Fig. 5 : AUC analyses using LSE Soft max approximation

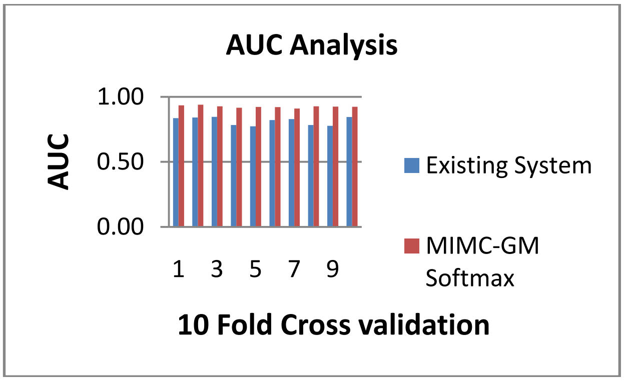

Fig. 6 : AUC analyses using GM Soft max approximation

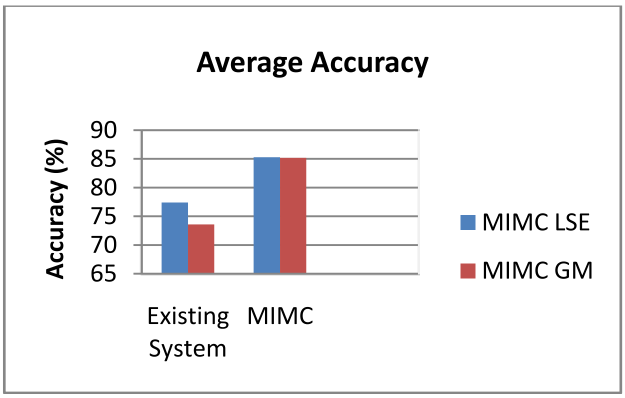

Fig. 7 : Comparative average mining and classification accuracy using GM and LSE Soft max

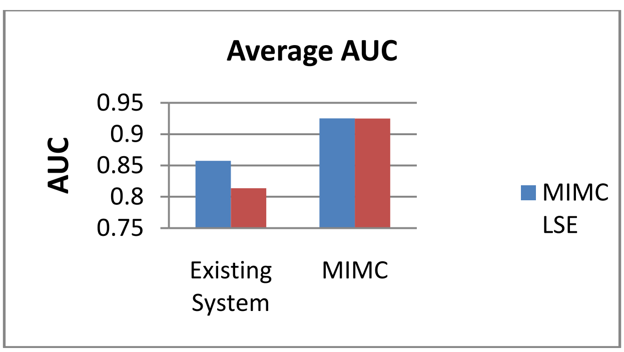

Fig. 8 : Comparative average AUC analysis using GM and LSE Soft max

The average performance analysis (Fig. 7 and Fig. 8) affirms that the proposed MIMC-MIL performs better with log-sum-exponential (LSE) soft max approximation than generalized model (GM) based approximation for ROI instance probability estimation. Overall performance exhibits that the proposed multi-instance multi-cluster (MIMC) algorithm with LSE soft max approximation for MIL can provide a novel solution for large scale multimedia data mining (MDM).

Table 4 : Comparative classification accuracy analysis

Mil Based MiningTechniques	Accuracy(%)
DD-SVM [5]	85.4
MILIS [16]	85.8
MIForest [26]	88.6
mi-SVM [27]	85.0
EM-DD [28]	87.4
MILES [29]	84.8
MILD [15]	83.3
Intra Clustering_DMIL [25]	84.2
Proposed MIMC-MIL	87.5

As depicted in Table IV, the proposed system exhibits better mining and resulting classification accuracy as compared to the other existing systems. The developed system with different benchmark data exhibits the MIMC-MIL based approach outperforms conventional MIL based boosting and hence affirms that our proposed MIMC-MIL scheme can significantly perform with huge un annotated data for multimedia mining applications. Literatures state that other algorithms such as MKL [24] usually takes several days of time to train a classifier even for 60 images, while our proposed system performs optimized classification of 360 images just within 20 minutes.

IV. Conclusion

The exponential rise in un annotated multimedia data has demanded researchers to develop certain efficient multimedia data mining (MDM) algorithm that can provide optimal mining performance with minimal complexity and computational overheads. With these motivations, in this paper a robust multi-instance, multi-cluster (MIMC) multiple instances learning (MIL) algorithm has been developed. With an intension to assure optimal mining and classification efficiency a robust region of interest (ROI) identification and verification model has been developed. To perform ROI verification, two soft max approximation techniques, generalized mean (GM) and log-sum-exponential (LSE) algorithm have been applied. These approximation models have been used to estimate the probability of an instance, whether it belongs to a bag or not. In addition, a weight factor has been introduced that signifies inter-relationship between neighbouring instances. It enables effective clustering, segmentation as well as classification. Interestingly, the proposed system justifies its robustness by segmentation, clustering and classification simultaneously. The performance evaluation with multimedia image datasets with 10 fold cross validation affirms that the proposed system performs better than existing clustering based approaches. Thus, the proposed mining model and classification system can be considered to be resilient to noise as well as more robust in terms of more effective segmentation and classification. The overall performance affirms that the proposed system can be effective to perform mining and classification for different multimedia data types.

References Références Referencias

1. Dietterich, T.G., Lathrop, R.H., Lozano-P´erez, T.: Solving the multiple instance problem with axis-parallel rectangles. Artif. Intell. Vol. 89 (1-2), (1997) 31–71
2. ndrews, S., Tsochantaridis, I., Hofmann, T.: Support vector machines for multiple-instance learning. In: NIPS. (2003) 1073–1080
3. Zhang, Q., Goldman, S.A., Yu, W., Fritts, J.: Content-based image retrieval using multiple instance learning. In: ICML. (2002) 682–689
4. Chen, Y., Bi, J., Wang, J.Z.: MILES: Multiple-instance learning via embedded instance selection. IEEE Trans. Vol. 28 (12) Pattern Anal. Mach. Intell. (2006), 1931–1947
5. Chen, Y., Wang, J.Z.: Image categorization by learning and reasoning with regions. J. Mach. Learn. Res. Vol.5, (2004) 913–939
6. Chang, C.C., Lin, C.J.: LIBSVM: A library for support vector machines (2001), software available at http://www.csie.ntu.edu.tw/˜cjlin/libsvm
7. Babenko, B., Yang, M.H., Belongie, S.: Visual tracking with online multiple instance learning. In: CVPR. (2009) 983–990
8. Leistner, C., Saffari, A., Bischof, H.: MI Forests: Multiple-instance learning with randomized trees. In: ECCV. (2010) 29–42
9. Csurka, G., Dance, C.R., Fan, L., Willamowski, J., Bray, C.: Visual categorization with bags of key points. In: ECCV Int. Workshop Stat. Learning in Comp. Vis. (2004)
10. Zhang, Q., Goldman, S.A.: EM-DD: An improved multi-instance learning technique. In: NIPS. (2002) 561–568
11. G¨artner, T., Flach, P.A., Kowalczyk, A., Smola, A.J.: Multi-instance kernels. In: ICML. (2002) 179–186
12. Li, M., Kwok, J., Lu, B.L.: Online multiple instance learning with no regret. In: CVPR. (2010) 1395 –1401
13. Wang, J., Zucker, J-D.: Solving multiple-instance problem: A lazy learning approach. In: ICML (2000)
14. Viola, P., Platt, J.C., Zhang, C.: Multiple instance boosting for object detection. In: NIPS. (2006) 1419–1426
15. Li, W.J., Yeung, D.Y.: MILD: Multiple-instance learning via disambiguation. IEEE Trans. on Knowl. and Data Eng. (2010) Vol.22, 76–89
16. Fu, Z., Robles-Kelly, A., Zhou, J.: MILIS: Multiple instance learning with instance selection. IEEE Trans. Pattern Anal. Mach. Intell (2010).
17. D. Zhang, F.Wang, L. Si, and T. Li. M3IC: maximum margin multiple instance clustering. In IJCAI, 2009.
18. P. Doll´ar, B. Babenko, S. Belongie, P. Perona, and Z. Tu. Multiple component learning for object detection. In ECCV, 2008.
19. Z.-H. Zhou and M.-L. Zhang. Multi-instance multilabel learning with application to scene classification. In NIPS, 2007.
20. Z.-J. Zha, T. Mei, J. Wang, G.-J. Qi, and Z. Wang. Joint multi-label multi instance learning for image classification. In CVPR, 2008.
21. P. A. Viola, J. Platt, and C. Zhang. Multiple instance boosting for object detection. In NIPS, 2005.
22. L. Mason, J. Baxter, P. Bartlett, and M. Frean. Boosting algorithms as gradient descent. In NIPS, 2000.
23. B. Babenko, P. Doll´ar, Z. Tu, and S. Belongie. Simultaneous learning and alignment: Multi-instance and multi-pose learning. In ECCV workshop on Faces in Real-Life Images, 2008.
24. A. Vedaldi, V. Gulshan, M. Varma, and A. Zisserman. Multiple kernels for object detection. In ICCV, 2009.
25. G. S., Girisha, K. Udaya Kumar. An Enhanced Semi-Supervised Multiple Instance Learning Scheme for Multimedia Data Mining. International Journal of Applied Engineering Research. Vol. 10 No.86 (2015). 348-354.
26. Kelly, D., McDonald, J., Markham, C.: Weakly Supervised Training of a Sign Language Recognition System Using Multiple Instance Learning Density Matrices. Systems, Man, and Cybernetics, Part B: Cybernetics, vol.41, no.2, IEEE Transactions on April (2011) 526-541
27. Cheng, H. L., Gondra, I.: A Novel Neural Network-Based Approach for Multiple Instance Learning. Computer and Information Technology (CIT), IEEE 10th International Conference on (2010) 451-456
28. Yuan, X., Wang, M., Song Y.: Concept-dependent image annotation via existence-based multiple-instance learning. Systems, Man and Cybernetics, IEEE International Conference on (2009) 4112-4117
29. Dijia W., Jinbo B., Boyer, K.: A min-max framework of cascaded classifier with multiple instance learning for computer aided diagnosis," Computer Vision and Pattern Recognition, IEEE Conference on (2009) 1359-1366.