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

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Abstract

The high pace rise in online as well as offline multimedia unannotated 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 unannotated 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 unannotated data with different features. The proposed system employs softmax approximation techniques with a novel loss factor and inter-instance distance based weight estimation scheme for instance probability substantiation in bags.

***Index terms*—** multimedia data mining, multiple instance learning, multi-instance, multi-cluster based mining.

1 I. Introduction

he 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.

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 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, multicluster 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.

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 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 ?? ?? = {?? ??1 , . . . , ?? ???? } and for ð ?"?ð ?"? cluster, the individual bag is associated with a label, which can be defined as ð ?"?ð ?"? ???? ð ?"?ð ?"? ? ?? = {?1, 1}. In other words, the individual instance ?ð ?" ð ?" ???? ? ??? in a bag ??? ???? ? ?? ?? ? possesses a true label ?ð ?"?ð ?"? ???? ð ?"?ð ?"? ? ??? as a hidden variable that remains unknown during feature mining and training for further classification.

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Volume XVI Issue III Version I A bag is labelled as positive when ð ?" ð ?" ???? belongs to the ð ?"?ð ?"? th cluster, i.e.ð ?"?ð ?"? ???? ð ?"?ð ?"? = 1. As already stated, a bag can be labelled as positive if minimum one instance is positive and belongs to the ð ?"?ð ?"? th cluster. Mathematically,ð ?"?ð ?"? ?? = ?????? ?? ?ð ?"?ð ?"? ???? ð ?"?ð ?"? ?**(1)**

where ?????? is similar to an OR operator because ð ?”?ð ?”? ???? ð ?”?ð ?”? ? ??, ?????? ?? ?ð ?”?ð ?”? ???? ð ?”?ð ?”? ? = 1 ?? ? ?? , provided?? ???? = 1. In general, the predominant objective of an MIL algorithm is to perform learning at instance-level classifier ??(ð ?” ð ?” ????) ? ?? ? ??. MIL intends to provide an efficient learning mode for splitting the positive instances into ?? clusters by means of ?? instance level classifiers??(ð ?” ð ?” ????) ? ?? ? ??. In this process, the labelled bags ð ?”?ð ?”? ?? are used in such a manner that ?????? ?? ?????? ð ?”?ð ?”? ??(ð ?” ð ?” ????) = ð ?”?ð ?”? ?? . Unlike conventional MIL approaches [21,22,23], we have introduced a loss function to estimate the optimal weak classifier response ?? ð ?”?ð ?”? ð ?”?ð ?”? : ?? ? ?? that significantly reduces the loss on training data. Mathematically, the loss function is given by:? ?? (??) = ? ? ð ?”?ð ?”? ?? ð ?”?ð ?”? ??=1 ?1(?? ?? = 1)??????ð ?”?ð ?”? ?? + 1ð ?”?ð ?”???=?1??????1?ð ?”?ð ?”???, and (2) ? ? (??) = ? ð ?”?ð ?”? ?? ? ð ?”?ð ?”? ???? (??,??)?? ?? ð ?”?ð ?”? ??=1 ?ð ?”?ð ?”? ???? ? ð ?”?ð ?”? ???? ? 2

where ð ?”?ð ?”? ?? represents the initial weight of the ?? th training data and 1(?) states certain index function. The variable ? ?? represents the group of the pairs of all the neighbouring instances in ?? th bag or training data. Here, ð ?”?ð ?”? ???? represents the weight on the patches, which is nothing else but the pair of instances (features). The variables ?? ???? represents the relative distance between ?? and ??. If the instances are closer, then they are assigned with higher weights. To estimate the respective weights ?ð ?”?ð ?”? ???? ? of the instances and patches, we have usedð ?”?ð ?”? ???? = ?????????? ???? ?. Thus, estimating the value of ð ?”?ð ?”? ???? , the cumulative loss function (CLF) (2) has been estimated using equation (3).?????? = ?(??) = ? ?? (??) + ??? ? (??)**(3)**

Here, ? ? (??) 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, ? ?? (??) states the typical negative log likelihood. Variable represents the weight associated Here, a soft max function ? â??” (ð ?”?ð ?”? â??”) has been considered that performs approximations of ?????? value overð ?”?ð ?”? = {ð ?”?ð ?”? 1 , . . . , ð ?”?ð ?”? ?? }. 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 ð ?”?ð ?”? = {ð ?”?ð ?”? 1 , . . . , ð ?”?ð ?”? ?? }. In addition, a factor named sharpness control factor (SCF), ð ?”?ð ?”? 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 **??**. Domain GM ? 1 ?? ? ð ?”?ð ?”? â??” ð ?”?ð ?”? ?? ? 1 ð ?”?ð ?”? ? â??” (ð ?”?ð ?”? â??”) = ð ?”?ð ?”? ?? ð ?”?ð ?”??1 ? ?? â??” ?? â??” [0, ?] LSE 1 ?? ???? 1 ?? ?(ð ?”?ð ?”?ð ?”?ð ?”? â??”) ?????? exp (ð ?”?ð ?”?ð ?”?ð ?”? ??) ? exp (ð ?”?ð ?”?) â??” [-?,?] ð ?”?ð ?”? ???? ð ?”?ð ?”? = ???2?? ???? ð ?”?ð ?”? ?**(6)**

where ?? ???? ð ?”?ð ?”? = ?? ð ?”?ð ?”? ?ð ?” ð ?” ???? ?.

Now, substituting ?????? with ??, the instance probability ð ?”?ð ?”? ?? in a class can be obtained asð ?”?ð ?”? ?? = ? ?? ?? ð ?”?ð ?”? ?ð ?”?ð ?”? ???? ð ?”?ð ?”? ?? = ? ??ð ?”?ð ?”? ?ð ?”?ð ?”? ???? ð ?”?ð ?”? ? = ? ??ð ?”?ð ?”? ????2?? ???? ð ?”?ð ?”? ??

where??(ð ?”?ð ?”?) = 1 1 + exp (?ð ?”?ð ?”?)

The optimal weighted error factor ?ð ?”?ð ?”? ???? ? and the derivative ??? ???? ???? ð ?”?ð ?”? can be obtained asð ?”?ð ?”? ???? ð ?”?ð ?”? = ???(??) ???? ???? ð ?”?ð ?”? = ? ???(??) ???? ?? ??ð ?”?ð ?”? ?? ??ð ?”?ð ?”? ???? ð ?”?ð ?”? ??ð ?”?ð ?”? ???? ð ?”?ð ?”? ???? ???? ð ?”?ð ?”? . (**8**)?? ð ?”?ð ?”? ? ?? ð ?”?ð ?”? + ?? ð ?”?ð ?”? ð ?”?ð ?”? ?? ð ?”?ð ?”? ð ?”?ð ?”?**(9)**

where ?? ð ?”?ð ?”? 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. ? â??” (ð ?”?ð ?”? â??”) ? max â??” (ð ?”?ð ?”? â??”) = ð ?”?ð ?”?, ??? â??” (ð ?”?ð ?”? â??”) ??ð ?”?ð ?”? ?? ? 1(ð ?”?ð ?”? ?? = ð ?”?ð ?”? *) ? 1 ?? (ð ?”?ð ?”? ?? = ð ?”?ð ?”? *) (**5**)

where, ?? = |ð ?”?ð ?”?|. To maintain simplified presentation, in rest of the paper, the variable ? â??” (ð ?”?ð ?”? â??”) has been represented by , while ð ?”?ð ?”? â??” is represented in terms of . In order to enhance the loss function , at first the probability ð ?”?ð ?”? ?? of bag is required to be estimated, which is stated to be the highest over ð ?”?ð ?”? ???? ð ?”?ð ?”? . Here, the probability that an instance ð ?” ð ?” ???? belongs to the ?? ??? cluster, is given by Thus, performing the optimization of weighed error factor?ð ?”?ð ?”? ???? ð ?”?ð ?”? ?, the weak classifier ?? ???? ð ?”?ð ?”? has been trained efficiently. Finally, a string classifier has been obtained as 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. (7) 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 (?? ?? = ????1, . . . , ?????? has been prepared and respective labelling of bags (ð ?”?ð ?”? ?? ? ?? = {?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 **??**I ð ?” ð ?” ?? = {ð ?” ð ?” ??1 , ? , ð ?” ð ?” ???? } ?? ???? ? ð ?” ð ?” ð ?” ð ?” ?? ? {?1,1}; ð ?” ð ?” ???? ? {?1,1} Proposed MIL ð ?” ð ?” ?? = {ð ?” ð ?” ??1 , ? , ð ?” ð ?” ???? } ð ?” ð ?” ???? ? ð ?” ð ?” ð ?” ð ?” ?? ? {?1,1}; ð ?” ð ?” ???? ? {?1,1} ð ?”?ð ?”?

???? ð ?”?ð ?”? ? ?ð ?”?ð ?”? ???? 1 , ? , ð ?”?ð ?”? ???? ð ?”?ð ?”? ?; ð ?”?ð ?”? ?? = ?? ?? ?ð ?”?ð ?”? ???? ? = ? â??” (? ð ?”?ð ?”? ?ð ?”?ð ?”? ???? ð ?”?ð ?”? ?**(11)**

where ð ?”?ð ?”? ???? ð ?”?ð ?”? represents the probability that the ROI or the concept region instance ð ?” ð ?” ???? belongs to the ð ?”?ð ?”? ??? cluster. The overall MIMC-MIL based mining and classification model is given in Fig. 1 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 ð ?” ð ?” ???? 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 (ð ?”?ð ?”? ???? = ð ?”?ð ?”? ?? , ?? = 1, . . . , ð ?”?ð ?”?, ?? = 1, . . . , ??) and thus based on the final clustering output the classification has been done.

3 ii. Segmentation

In multimedia mining applications, especially when there are huge data, it becomes too intricate, 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 (?? instance-level) classification has been done ?? ð ?”?ð ?”? ?ð ?” ð ?” ???? ?: ?? ? ?? for ??clusters. Consequently, the baglevel classifier for certain ð ?”?ð ?”? th cluster has been formed as?? ð ?”?ð ?”? (ð ?” ð ?” ??) ? ?? ?? ? ??. Thus, the overall classification approach for MDM can be stated as?(ð ?” ð ?” ??) ? ?? ?? ? ??.

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?(ð ?” ð ?” ??) = max ð ?”?ð ?”? ?? ð ?”?ð ?”? (ð ?” ð ?” ??) max ð ?”?ð ?”? max ?? ?? ð ?”?ð ?”? ?ð ?” ð ?” ???? ?**(10)**

As an optimization of our previous work [25], in this paper the ROI probability factor ð ?”?ð ?”? ?? has been estimated in terms of the softmax of ð ?”?ð ?”? ???? ? ??(ð ?”?ð ?”? ???? = 1|ð ?”?ð ?”? ????) for all the associated instances in the bags (image dataset). ROI instance probability ?ð ?”?ð ?”? ???? ? in a bag (bag represents the image having multiple clusters, where clusters are formed by instances) has been estimated ?ð ?”?ð ?”? ???? ð ?”?ð ?”? = ??(ð ?”?ð ?”? ???? ð ?”?ð ?”? = 1|ð ?” ð ?” ????)? using LSE and GM based soft max approximation technique. The eventual instance probability is obtained as: 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 training subset. Our proposed algorithm generates probability mapping for all instances (ð ?”?ð ?”? ??) associated with bag ?? ?? . Thus, implementing MIMC-MIL classifier, the parameters such as accuracy, recall and Fmeasures have been estimated. F-measure factor 2.

5 Precision $\times$Recall

Precision +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 Kmeans algorithm to perform clustering of the positive instances (concept region or ROI).

6 III.

7 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 **??**II. 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. The average performance analysis (Fig. **??** and Fig. **??**) 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 multiinstance multi-cluster (MIMC) algorithm with LSE soft max approximation for MIL can provide a novel solution for large scale multimedia data mining (MDM).

8 Table 4 : Comparative classification accuracy analysis

As depicted in Table IV, the proposed system 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.

9 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, multicluster (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 interrelationship between neighbouring instances. It enables 5M: Multi-Instance Multi-Cluster based Weakly Supervised MIL Model for Multimedia Data Mining 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

Mil Based MiningTechniques Accuracy(%) DD-SVM [5] 85.4

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. [1]

Figure 1:

1 

Figure 2: Fig. 1 :

Figure 3:

Multimedia data

SIVAL Data (360 Images)

180 Positive Bags

180 Negative Bags

Feature extraction and Initial Bag Generation

Initial Clustering

A1 B1 C1 Z1

A2 B2 C2 Z2

A3 B3 C3 Z3

Year x1 x2 Instance Verification Model x3 x4

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Yij ? X?

18 LSE/GM Softmax Approximation Loss Function

Inter-instance distance based weight factor

Multi-Instance Multi-Cluster (MIL) Based MIL for Classification and

10 fold Cross Validation

A1 A2 A3 B1 B2 B3 C1 C2 C3 Z1 x1

Z2 x2

Z3 x3

x4

Performance Evaluation for Mining and Classification

( )

Figure 4: C

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where, ?? ð ?"?ð ?"? ? ? ???? ???(??) ??? ???? ð ?"?ð ?"? .

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Figure 5:

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Figure 6: Table 1 :

2

TECHNIQUE	TRAINING DATA	OBJECTIVE
		ð ?" ð ?" ?? ? ???????????????????????????? ð ?" ð ?" ???? ? ???????????????????????? ð ?"?ð ?"? ???? ð ?"?ð ?"? ? ???????????????????
Standard	ð ?" ð ?" ??	ð ?" ð ?" ?? ? {?1,1}
Classifier Conventional MIL		

Figure 7: Table 2 :

Calculate weights ð ?"?ð ?"? ???? ð ?"?ð ?"? = ?(??) = ? ?? (??) + ??? ? (??)

? ???(??) ???? ???? ð ?"?ð ?"? = ? ??? ?? (??) ???? ?? ??ð ?"?ð ?"?ð ?"?ð ?"? ?? ???? ??ð ?"?ð ?"?ð ?"?ð ?"? ???? ???? ð ?"?ð ?"??? ð ?"?ð ?"? + ??

ð ?"?ð ?"? using Perform training of the weak classifier ?? ð ?"?ð ?"? weights ð ?"?ð ?"? ???? ð ?"?ð ?"? ?? ð ?"?ð ?"? ð ?"?ð ?"? = ?????? min ?? ???? ? 1????ð ?" ð ?" ???? ð

Update strong classifier ?? ð ?"?ð ?"? ? ?? ð ?"?ð ?"? + ?? ð ?"?ð ?"? ð ?"?ð ?"? ?? ð ?"?ð ?"? ð ?"?ð ?"?

Form final cluster with ROI/ verified instances

end for

end for

Figure 8: .

3

Figure 9: Table 3 :

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