AN IMPROVED IMAGE RETRIEVAL TECHNIQUE APPLIED IN ONLINE MULTI-MODAL DISTANCE METRIC LEARNING

1. VANGALA. NARASIMHA
UG Scholar, Dept. Of CSE, CMR Technical Campus, Hyderabad

2. REGONDA. NAGARAJU
Associate Professor, Dept. Of CSE, CMR Technical Campus, Hyderabad

3.Md.NASEEB KHAN
UG Scholar, Dept. Of CSE, CMR Technical Campus, Hyderabad

4. B. PRIYANKA UG Scholar, Dept. Of CSE, CMR Technical Campus, Hyderabad

ABSTRACT:-

Distance metric learning (DML) is an important technique to improve similarity search in content-based image retrieval. Despite being studied extensively, most existing DML approaches typically adopt a single-modal learning framework that learns the distance metric on either a single feature type or a combined feature space where multiple types of features are simply concatenated. Such single-modal DML methods suffer from some critical limitations: (i) some type of features may significantly dominate the others in the DML task due to diverse feature representations; and (ii) learning a distance metric on the combined high-dimensional feature space can be extremely time-consuming using the naive feature concatenation approach. To address these limitations, in this paper, we investigate a novel scheme of online multi-modal distance metric learning (OMDML), which explores a unified two-level online learning scheme: (i) it learns to optimize a distance metric on each individual feature space; and (ii) then it learns to find the optimal combination of diverse types of features. To further reduce the expensive cost of DML on high-dimensional feature space, we propose a low-rank OMDML algorithm which not only significantly reduces the computational cost but also retains highly competing or even better learning accuracy. We conduct extensive experiments to evaluate the performance of the proposed algorithms for multi-modal image retrieval, in which encouraging results validate the effectiveness of the proposed technique.

***Keywords**:-Distance metric learning,multi-modal distance metric learning,multi-modal image retrieval, content-based image retrieval (CBIR) systems, Hedge Algorithms.*

INTRODUCTION:-

One of the core research problems in multimedia retrieval is to seek an effective distance metric function for computing similarity of two objects in content-based multimedia retrieval tasks. Over the past decades, multimedia researchers have spent much effort in designing a variety of low-level feature representations and different distance measures. Finding a good distance metric/function remains an open challenge for content-based multimedia retrieval tasks till now. In recent years, one promising direction to address this challenge is to explore distance metric learning (DML) by applying machine learning techniques to optimize distance metrics from training data or side information, such as historical logs of user relevance feedback in content-based image retrieval (CBIR) systems. Although various DML algorithms have been proposed in literature most existing DML methods in general belong to single-modal DML in that they learn a distance metric either on a single type of feature or on a combined feature space by simply concatenating multiple types of diverse features together. In a real-world application, such approaches may suffer from some practical limitations: (i) some types of features may significantly dominate the others in the DML task, weakening the ability to exploit the potential of all features; and (ii) the naive concatenation approach may result in a combined high-dimensional feature space, making the subsequent DML task computationally intensive. To overcome the above limitations, in this project, we investigate a novel framework of Online Multi-modal Distance Metric Learning (OMDML), which aims to learn distance metrics from multi-modal data or multiple types of features via an efficient and scalable online learning scheme.

1. IMPLEMENTATION MODULES:-

1. Content based Image Retrieval
2. Distance Metric Learning
3. Online Learning

Content-based Image Retrieval:-

With the rapid growth of digital cameras and photo sharing websites, image retrieval has become one of the most important research topics in the past decades, among which content based image retrieval is one of key challenging problems [1], [2], [3]. The objective of CBIR is to search images by analyzing the actual contents of the image as opposed to analyzing metadata like keywords, title and author, such that extensive efforts have been done for investigating various low-level feature descriptors for image representation [14]. For example, researchers have spent many years in studying various global features for image representation, such as color features [14], edge features [14], and texture features [15]. Recent years also witness the surge of research on local feature based representation, such as the bag-of-words models [16], [17] using local feature descriptors (e.g., SIFT [18]). Conventional CBIR approaches usually choose rigid distance functions on some extracted low-level features for multimedia similarity search, such as the classical Euclidean distance or cosine similarity. However, there exists one key limitation that the fixed rigid similarity/distance function may not be always optimal because of the complexity of visual image representation and the main challenge of the semantic gap between the low-level visual features extracted by computers and high-level human perception and interpretation. Hence, recent years have witnesses a surge of active research efforts in design of various distance/similarity measures on some lowlevel features by exploiting machine learning techniques [19], [20], [21], among which some works focus on learning to hash for compact codes [22], [19], [23], [24], [25], and some others can be categorized into distance metric learning that will be introduced in the next subsection. Our work is also related to multimodal/multiview studies, which have been widely studied on image classification and object recognition fields [26], [27], [28], [29]. However, it is usually hard to exploit these techniques directly on CBIR because (i) in general, image classes will not be given explicitly on CBIR tasks, (ii) even if classes are given, the number will be very large, (iii) image datasets tend to be much larger on CBIR than on classification tasks. We thus exclude the direct comparisons to such existing works in this paper. There are still some other open issues in CBIR studies, such as the efficiency and scalability of the retrieval process that often requires an effective indexing scheme, which are out of this paper's scope.

Distance Metric Learning:-

Distance metric learning has been extensively studied in both machine learning and multimedia retrieval communities [30], [7], [31], [32], [33], [34], [35], [36]. The essential idea is to learn an optimal metric which minimizes the distance between similar/related images and simultaneously maximizes the distance between dissimilar / unrelated images. Existing DML studies can be grouped into different categories according to different learning settings and principles. For example, in terms of different types of constraint settings, DML techniques are typically categorized into two groups:

• Global supervised approaches [30], [7]: to learn a metric on a global setting, e.g., all constraints will be satisfied simultaneously;

• Local supervised approaches [32], [33]: to learn a metric in the local sense, e.g., the given local constraints from neighboring information will be satisfied.

Moreover, according to different training data forms, DML studies in machine learning typically learn metrics directly from explicit class labels [32], while DML studies in multimedia mainly learn metrics from side information, which usually can be obtained in the following two forms:

• Pairwise constraints [7], [9]: A must-link constraint set S and a cannot-link constraint set D are given, where a pair of images (pi, pj) ∈ S if pi is related/similar to pj , otherwise (pi, pj) ∈ D. Some literature uses the term equivalent/positive constraint in place of "mustlink", and the term inequivalent/negative constraint in place of "cannot-link".

• Triple constraints [20]: A triplet set P is given, where P = {(pt, p+ t , p−t)|(pt, p+t) ∈ S; (pt, p−t) ∈ D, t =1, . . . , T }, S contains related pairs and D contains unrelated pairs, i.e., p is related/similar to p+ and p is unrelated/dissimilar to p−. T denotes the cardinality of entire triplet set. When only explicit class labels are provided, one can also construct side information by simply considering relationships of instances in same class as related, and relationships of instances belonging to different classes as unrelated. In our works, we focus on triple constraints. Finally, in terms of learning methodology, most existing DML studies generally employ batch learning methods which often assume the whole collection of training data must be given before the learning task and train a model from scratch, except for a few recent DML studies which begin to explore online learning techniques [37], [38]. All these works generally address single modal DML, which is different from our focus on multi-modal DML.We also note that our work is very different from the existing multiview DML study [26] which is concerned with regular classification tasks by learning a metric on training data with explicit class labels, making it difficult to be compared with our method directly. We note that our work is different from another multimodal learning study in [39] which addresses a very different problem of search-based face annotation where their multimodal learning is formulated with a batch learning task for optimizing a specific loss function tailored for search-based face annotation tasks from weakly labeled data. Finally, we note that our work is also different from some existing distance learning studies that learn nonlinear distance functions using kernel or deep learning methods [21], [40], [35]. In comparison to the linear distance metric learning methods, kernel methods usually may achieve better learning accuracy in some scenarios, but falls short in being difficult to scale up for large-scale applications due to the curse of kernelization, i.e., the learning cost increases dramatically when the number of training instances increases. Thus, our empirical study is focused on direct comparisons to the family of linear methods.

Online Learning:-

Our work generally falls in the category of online learning methodology, which has been extensively studied in machine learning [41], [42]. Unlike batch learning methods that usually suffer from expensive re-training cost when new training data arrive, online learning sequentially makes a highly efficient (typically constant) update for each new training data, making it highly scalable for large-scale applications. In general, online learning operates on a sequence of data instances with time stamps. At each time step, an online learning algorithm processes an incoming example by first predicting its class label; after the prediction, it receives the true class label which is then used to measure the suffered loss between the predicted label and the true label; at the end of each time step, the model is updated with the loss whenever it is nonzero. The overall objective of an online learning task is to minimize the cumulative loss over the entire sequence of received instances.

In literature, a variety of algorithms have been proposed for online learning [43], [44], [45], [46], [47]. Some well-known examples include the Hedge algorithm for online prediction with expert advice [48], the Perceptron algorithm [43], the family of passive-Aggressive (PA) learning algorithms [44], and the online gradient descent algorithms [49]. There is also some study that attempts to improve the scalability of online kernel methods, such as [50] which proposed a bounded online gradient descent for addressing online kernel-based classification tasks. In this work, we apply online learning techniques, i.e., the Hedge, PA, and online gradient descent algorithms, to tackle the multi-modal distance metric learning task for content-based image retrieval. Besides, we note that this work was partially inspired by the recent study of online multiple kernel learning which aims to address online classification tasks using multiple kernels [51]. In the following, we give a brief overview of several popular online learning algorithms.

Hedge Algorithms

The Hedge algorithm [48], [52] is a learning algorithm which aims to dynamically combine multiple strategies in an optimal way, i.e., making the final cumulative loss asymptotically approach that of the best strategy. Its key idea is to maintain a dynamic weigh-distribution over the set of strategies. During the online learning process,the distribution is updated according to the performance of those strategies. Specifically, the weight of every strategy is decreased exponentially with respect to its suffered loss, making the overall strategy approaching the best strategy.

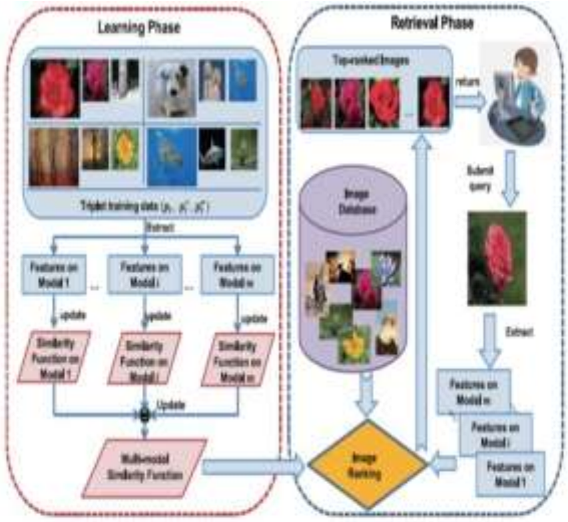
Passive-Aggressive Learning

As a classical well-known online learning technique, the Perceptron algorithm [43] simply updates the model by adding an incoming instance with a constant weight whenever it is misclassified. Recent years have witnessed a variety of algorithms proposed to improve Perceptron [53], [44], which usually follow the principle of maximum margin learning in order to maximize the margin of the classifier. Among them, one of the most notable approaches is the family of Passive-Aggressive (PA) learning algorithms [44], which updates the model whenever the classifier fails to produce a large margin on the incoming instance. In particular, the family of online PA learning is formulated to trade off the minimization of the distance between the target classifier and the previous classifier, and the minimization of the loss suffered by the target classier on the current instance. The PA algorithms enjoy good efficiency and scalability due to their simple closed-form solutions. Finally, both theoretical analysis and most empirical studies demonstrate the advantages of the PA algorithms over the classical Perceptron algorithm.

Online Gradient Descent:

Besides Perceptron and PA methods, another well-known online learning method is the family of Online Gradient Descent (OGD) algorithms, which applies the family of online convex optimization techniques to optimize some particular objective function of an online learning task [49]. It enjoys solid theoretical foundation of online convex optimization, and thus works effectively in empirical applications. When the training data is abundant and computing resources are comparatively scarce, some existing studies showed that a properly designed OGD algorithm can asymptotically approach or even outperform a respective batch learning algorithm [54].

2. System architecture:



3. Online Multi-modal Distance Metric Learning:

In literature, many techniques have been proposed to improve the performance of CBIR. Some existing studies have made efforts on investigating novel low-level feature descriptors in order to better represent visual content of images, while others have focused on the investigation of designing or learning effective distance/similarity measures based on some extracted low-level features. In practice, it is hard to find a single best low-level feature representation that consistently beats the others at all scenarios. Thus, it is highly desirable to explore machine learning techniques to automatically combine multiple types of diverse features and their respective distance measures. We refer to this open research problem as a multimodal distance metric learning task, and present two new algorithms to solve it in this section. The system flow of the proposed multi-modal distance metric learning scheme for content-based image retrieval, which consists of two phases, i.e., learning phase and retrieval phase. The goal is to learn the distance metrics in the learning phase in order to facilitate the image ranking task in the retrieval phase. We note that these two phases may operate concurrently in practice, where the learning phase may never stop by learning from endless stream training data. During the learning phase, we assume triplet training data instances arrive sequentially, which is natural for a real-world CBIR system. For example, in online relevance feedback, a user is often asked to provide feedback to indicate if a retrieved image is related or unrelated to a query; as a result, users' relevance feedback log data can be collected to generate the training data in a sequential manner for the learning task [55]. Once a triplet of images is received, we extract different lowlevel feature descriptors on multiple modalities from these images. After that, every distance function on a single modality can be updated by exploiting the corresponding features and label information. Simultaneously, we also learn the optimal combination of different modalities to obtain the final optimal distance function, which is applied to rank images in the retrieval phase. During the retrieval phase, when the CBIR system receives a query from users, it first applies the similar approach to extract low-level feature descriptors on multiple modalities, then employs the learned optimal distance function to rank the images in the database, and finally presents the user with the list of corresponding top-ranked images. In the following,we first give the notation used throughout the rest of this paper, and then formulate the problem of multi-modal distance metriclearning followed by presenting online algorithms to solve it.

Notation:-

For the notation used in this paper, we use bold upper case letter to denote a matrix, for example, $M \in Rn\times n$, and bold lower case letter to denote a vector, for example, $p \in Rn$. We adopt I to denote an identity matrix. Formally, we define the following terms and operates:

• m: the number of modalities (types of features).

• ni: the dimensionality of the i-th visual feature space (modality).

• p(i): the i-th type of visual feature (modality) of the corresponding image $p(i) \in Rni$.

• M(i): the optimal distance metric on the i-th modality, where $M(i) \in Rni\times ni$.

• W(i): a linear transformation matrix by decomposing M(i), such that, M(i) = W(i)T W(i), $Wi \in Rri\times ni$, where ri is the dimensionality of projected feature space.

• S: a positive constraint set, where a pair $(pi, pj) \in S$ if and only if pi is related/similar to pj .

• D: a negative constraint set, where a pair $(pi, pj) \in S$ if and only if pi is unrelated/dissimilar to pj .

• P: a triplet set, where $P = \{(pt, p+t , p-t)|(pt, p+t) \in S; (pt, p-t) \in D, t = 1, . . . , T \}$, where T denotes the cardinality of entire triplet set.

• di(p2, p2): the distance function of two images p1 and p2 on the i-th type of visual feature (modality). When only one modality is considered, we will omit the superscript (i) or subscript i in the above terms.

4. Algorithm:-

INPUT:
- Discount weight: $\beta \in (0,1)$
- regularization parameter: $C > 0$
- margin parameter: $\gamma \geq 0$

Initialization:
- $\theta_1^{(i)} = 1/m, \forall i = 1, \ldots, m$
- $\mathrm{M}_{b1}^{(i)} = \mathbb{I}, \forall i = 1, \ldots, m$

for $t = 1, 2, \ldots, T$ **do**
  Receive: $(\mathrm{p}_t, \mathrm{p}_t^+, \mathrm{p}_t^-)$
  $f_t^{(i)} = d_i(\mathrm{p}_t, \mathrm{p}_t^+) - d_i(\mathrm{p}_t, \mathrm{p}_t^-), \forall i = 1, \ldots, m$
  $f_t = \sum_{i=1}^m \theta_t^{(i)} f_t^{(i)}$
  if $f_t + \gamma > 0$ **then**
    for $i = 1, 2, \ldots, m$ **do**
      Set $z_t^{(i)} = \mathbb{I}(f_t^{(i)} > 0)$
      Update $\theta_{t+1}^{(i)} \leftarrow \theta_t^{(i)} \beta^{z_t^{(i)}}$
      Update $\mathrm{M}_{t+1}^{(i)} \leftarrow \mathrm{M}_t^{(i)} - \tau_t^{(i)} \mathrm{V}_t^{(i)}$ by Eq. (5)
      Update $\mathrm{M}_{t+1}^{(i)} \leftarrow PSD(\mathrm{M}_{t+1}^{(i)})$
    end for
    $\Theta_{t+1} = \sum_{i=1}^m \theta_{t+1}^{(i)}$
    $\theta_{t+1}^{(i)} \leftarrow \theta_{t+1}^{(i)} / \Theta_{t+1}, \forall i = 1, \ldots, m$
  end if
end for

5. CONCLUSION:-

This paper investigated a novel family of online multi-modal distance metric learning (OMDML) algorithms for CBIR tasks with the exploitation of multiple types of features. We pinpointed the serious limitations of traditional DML approaches in practice, and presented the online multi-modal DML method which simultaneously learns both the optimal distance metric on each individual feature space and the optimal combination of the metrics on multiple types of features. We further proposed the low-rank online multi-modal DML algorithm (LOMDML), which not only runs more efficiently and scalably, but also attains the state-of-the-art performance among all the competing algorithms as observed from our extensive set of experiments. Our future work will extend the proposed framework for learning non-linear distance functions.

REFERENCES:-

[1] M. S. Lew, N. Sebe, C. Djeraba, and R. Jain, "Content-based multimedia information retrieval: State of the art and challenges," MultimediaComputing, Communications and Applications, ACM Transactions on,vol. 2, no. 1, pp. 1–19, 2006.

[2] Y. Jing and S. Baluja, "Visualrank: Applying pagerank to large-scale image search," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 30, no. 11, pp. 1877–1890, 2008.

[3] D. Grangier and S. Bengio, "A discriminative kernel-based approach to rank images from text queries," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 30, no. 8, pp. 1371–1384, 2008.

[4] A. K. Jain and A. Vailaya, "Shape-based retrieval: a case study with trademark image database," Pattern Recognition, no. 9, pp. 1369–1390, 1998.

[5] Y. Rubner, C. Tomasi, and L. J. Guibas, "The earth movers distance as a metric for image retrieval," International Journal of Computer Vision, vol. 40, p. 2000, 2000.

[6] A. W. M. Smeulders, M. Worring, S. Santini, A. Gupta, and R. Jain, "Content-based image retrieval at the end of the early years," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 22, no. 12, pp. 1349–1380, 2000.

[7] S. C. Hoi, W. Liu, M. R. Lyu, and W.-Y. Ma, "Learning distance metrics with contextual constraints for image retrieval," in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, New York, US, Jun. 17–22 2006, dCA.

[8] L. Si, R. Jin, S. C. Hoi, and M. R. Lyu, "Collaborative image retrieval viaregularized metric learning," ACM Multimedia Systems Journal, vol. 12, no. 1, pp. 34–44, 2006.

[9] S. C. Hoi, W. Liu, and S.-F. Chang, "Semi-supervised distance metric learning for collaborative image retrieval," in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, Jun. 2008.

[10] G. H. J. Goldberger, S. Roweis and R. Salakhutdinov, "Neighbourhood components analysis," in Advances in Neural Information Processing Systems, 2005.

[11] K. Fukunaga, Introduction to Statistical Pattern Recognition. Elsevier,1990.

[12] A. Globerson and S. Roweis, "Metric learning by collapsing classes," in Advances in Neural Information Processing Systems, 2005.

[13] L. Yang, R. Jin, R. Sukthankar, and Y. Liu, "An efficient algorithm for local distance metric learning," in Association for the Advancement of Artificial Intelligence, 2006.

[14] A. K. Jain and A. Vailaya, "Image retrieval using color and shape," Pattern Recognition, vol. 29, pp. 1233–1244, 1996.

[15] B. S. Manjunath and W.-Y. Ma, "Texture features for browsing and retrieval of image data," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 18, no. 8, pp. 837–842, 1996.

[16] J. Sivic, B. C. Russell, A. A. Efros, A. Zisserman, and W. T. Freeman, "Discovering objects and their location in images," in IEEE Conference on Computer Vision and Pattern Recognition, 2005.

[17] J. Yang, Y.-G. Jiang, A. G. Hauptmann, and C.-W. Ngo, "Evaluating bag-of-visual-words representations in scene classification," in ACM International Conference on Multimedia Information Retrieval, 2007, pp. 197–206.

[18] D. G. Lowe, "Object recognition from local scale-invariant features," in IEEE International Conference on Computer Vision, 1999, pp. 1150–1157.

[19] R. S. Mohammad Norouzi, David Fleet, "Hamming distance metric learning," in Advances in Neural Information Processing Systems, 2012.

[20] G. Chechik, V. Sharma, U. Shalit, and S. Bengio, "Large scale online learning of image similarity through ranking," Journal of Machine Learning Research, vol. 11, pp. 1109–1135, 2010.

[21] H. Chang and D.-Y. Yeung, "Kernel-based distance metric learning for content-based image retrieval," Image and Vision Computing, vol. 25, no. 5, pp. 695–703, 2007.

[22] R. Salakhutdinov and G. Hinton, "Semantic hashing," International Journal of Approximate Reasoning, vol. 50, no. 7, pp. 969–978, Jul. 2009. [Online]. ttp://dx.doi.org/10.1016/j.ijar.2008.11.006

[23] H. Jegou, F. Perronnin, M. Douze, J. Sanchez, P. Perez, and C. Schmid, "Aggregating local image descriptors into compact codes," IEEE Trans. Pattern Anal. Mach. Intell., vol. 34, no. 9, pp. 1704–1716, Sep. 2012 [Online]. Available: http://dx.doi.org/10.1109/TPAMI.2011.235

[24] K. Chatfield, V. S. Lempitsky, A. Vedaldi, and A. Zisserman, "The devil is in the details: an evaluation of recent feature encoding methods," in BMVC, 2011, pp. 1–12.

[25] A. Joly and O. Buisson, "Random maximum margin hashing," in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR'11), Washington, DC, USA, 2011, pp. 873–880.

[26] D. Zhai, H. Chang, S. Shan, X. Chen, and W. Gao, "Multiview metric learning with global consistency and local smoothness," ACM Trans. On Intelligent Systems and Technology, vol. 3, no. 3, p. 53, 2012.

[27] W. Di and M. Crawford, "View generation for multiview maximum disagreement based active learning for hyperspectral image classification," Geoscience and Remote Sensing, IEEE Transactions on, vol. 50, no. 5, pp. 1942–1954, 2012.

[28] S. Akaho, "A kernel method for canonical correlation analysis," in In Proceedings of the International Meeting of the Psychometric Society. Springer-Verlag, 2001.

[29] J. D. R. Farquhar, H. Meng, S. Szedmak, D. R. Hardoon, and J. Shawetaylor, "Two view learning: Svm-2k, theory and practice," in Advances in Neural Information Processing Systems. MIT Press, 2006.

[30] A. Bar-Hillel, T. Hertz, N. Shental, and D. Weinshall, "Learning distance functions using equivalence relations," in Proceedings of International Conference on Machine Learning, 2003, pp. 11–18.

[31] J.-E. Lee, R. Jin, and A. K. Jain, "Rank-based distance metric learning: An application to image retrieval," in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, Anchorage, AK, 2008.

[32] K. Weinberger, J. Blitzer, and L. Saul, "Distance metric learning for large margin nearest neighbor classification," in Advances in Neural Information Processing Systems, 2006, pp. 1473–1480.

[33] C. Domeniconi, J. Peng, and D. Gunopulos, "Locally adaptive metric nearest-neighbor classification," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 24, no. 9, pp. 1281 – 1285, 2002.

[34] P. Wu, S. C. H. Hoi, P. Zhao, and Y. He, "Mining social images with distance metric learning for automated image tagging," in

Proceedings of the fourth ACM international conference on Web search and data mining. ACM, 2011, pp. 197–206.

[35] P. Wu, S. C. Hoi, H. Xia, P. Zhao, D. Wang, and C. Miao, "Online multimodal deep similarity learning with application to image retrieval," in Proceedings of the 21st ACM international conference on Multimedia. ACM, 2013, pp. 153–162.

[36] X. Gao, S. C. Hoi, Y. Zhang, J. Wan, and J. Li, "Soml: Sparse online metric learning with application to image retrieval," in Proceedings of the Twenty-Eighth AAAI Conference on Artificial Intelligence, 2014.

[37] P. Jain, B. Kulis, I. S. Dhillon, and K. Grauman, "Online metric learning and fast similarity search," in Advances in Neural Information Processing Systems, 2008, pp. 761–768.

[38] R. Jin, S. Wang, and Y. Zhou, "Regularized distance metric learning: Theory and algorithm," in Advances in Neural Information Processing Systems, 2009, pp. 862–870.

[39] D. Wang, S. C. H. Hoi, P. Wu, J. Zhu, Y. He, and C. Miao, "Learning to name faces: a multimodal learning scheme for search-based face annotation," in SIGIR, 2013, pp. 443–452.

[40] H. Xia, P. Wu, and S. C. H. Hoi, "Online multi-modal distance learning for scalable multimedia retrieval," in WSDM, 2013, pp. 455–464.

[41] S. Shalev-Shwartz, "Online learning and online convex optimization," Foundations and Trends in Machine Learning, vol. 4, no. 2, pp. 107–194, 2011.

[42] S. C. Hoi, J. Wang, and P. Zhao, "Libol: A library for online learning algorithms," Journal of Machine Learning Research, vol. 15, pp. 495–499, 2014. Available: https://github.com/LIBOL

[43] F. Rosenblatt, "The perceptron: A probabilistic model for information storage and organization in the brain," Psychological Review, vol. 7, pp. 551–585, 1958.

[44] K. Crammer, O. Dekel, J. Keshet, S. Shalev-Shwartz, and Y. Singer, "Online passive-aggressive algorithms," Journal of Machine Learning Research, vol. 7, pp. 551–585, 2006.

[45] M. Dredze, K. Crammer, and F. Pereira, "Confidence-weighted linear classification," in Proceedings of International Conference on Machine Learning, 2008, pp. 264–271.13

[46] K. Crammer, A. Kulesza, and M. Dredze, "Adaptive regularization of weight vectors," in Advances in Neural Information Processing Systems, 2009, pp. 414–422.

[47] P. Zhao, S. C. H. Hoi, and R. Jin, "Double updating online learning," Journal of Machine Learning Research, vol. 12, pp. 1587–1615, 2011.

[48] Y. Freund and R. E. Schapire, "A decision-theoretic generalization of on-line learning and an application to boosting," Journal of Computer and System Sciences, vol. 55, no. 1, pp. 119–139, 1997.

[49] M. Zinkevich, "Online convex programming and generalized infinitesimal gradient ascent," in Proceedings of International Conference on Machine Learning, 2003, pp. 928–936.

[50] S. C. H. Hoi, J. Wang, P. Zhao, R. Jin, and P. Wu, "Fast bounded online gradient descent algorithms for scalable kernel-based online learning," in ICML, 2012.

[51] S. C. Hoi, R. Jin, P. Zhao, and T. Yang, "Online multiple kernel classification," Machine Learning, vol. 90, no. 2, pp. 289–316, 2013.

[52] Y. Freund and R. E. Schapire, "Adaptive game playing using multiplicative weights," Games and Economic Behavior, vol. 29, no. 1, pp.79–103, 1999.

[53] Y. Li and P. M. Long, "The relaxed online maximum margin algorithm," in Advances in Neural Information Processing Systems, 1999, pp. 498–504.

[54] L. Bottou and Y. LeCun, "Large scale online learning," in Advances in Neural Information Processing Systems, 2003.

[55] S. C. Hoi, M. R. Lyu, and R. Jin, "A unified log-based relevance feedback scheme for image retrieval," Knowledge and Data Engineering, IEEE Transactions on, vol. 18, no. 4, pp. 509–204, 2006.

[56] G. Griffin, A. Holub, and P. Perona, "Caltech-256 object category dataset," California Institute of Technology, Tech. Rep. 7694, 2007.

[57] A. Quattoni and A. Torralba, "Recognizing indoor scenes," in IEEE Conference on Computer Vision and Pattern Recognition, 2009.

Author's Profile:

*1. **Vangala.Narasimha**, Presently Pursuing B.Tech.,CSE in CMR Technical campus, Hyderabad, Telangana, INDIA. His interesting domains are Network Security, Cloud Computing, Image Processing,etc.*

*2. **Regonda.Nagaraju** presently working as an Associate Professor in CMR Technical campus,*

Hyderabad, Telangana, INDIA. He received his M.Tech (CSE) degree from JNTU Hyderabad in the year 2011.He received B.Tech. (CSE) degree from JNTU Hyderabad, in the year 2006. His interesting domains are Image Processing, Machine learning, Network Security, Cloud Computing, Internet of Things(IOT) ,etc.

***3.Md.Naseeb Khan** presently Pursuing B.Tech.,CSE in CMR Technical campus, Hyderabad, Telangana, INDIA. His interesting domains are Network Security, Cloud Computing, Image Processing,etc*

***4.B.Priyanka** presently Pursuing B.Tech.,CSE in CMR Technical campus, Hyderabad, Telangana, INDIA. Her interesting domains are Network Security, Cloud Computing, Image Processing,etc*