A Hybrid Procreative –Discriminative Based Hashing Method

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***Abstract**:* Hashing method is the one of the main method for searching same and different images based on hash code.For capturing similarities between textual, visual and cross media information; a hashing approaches have been proven. To address these challenges, in this paper we propose semantic level cross media hashing (SCMH) and deep belief network (DBN) is for a co-relation between different modalities.

Keywords: *Hashing method, fisher vector, word embedding.*

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I. INTRODUCTION

Hashing method is one of the method for searching a same and different images based on hashing code. A mixed generative discriminative is the one of the searching type of image, means we in this we can search a both type of images by using the search keyword, it is helpful for display a combination of both content type and image type searches. Hashing-based methods, which create compact hash codes that preserve similarity, for single-model or cross-model retrieval on large-scale databases have attracted considerable attention [1], [2], [3], [4], [5], [6]**.** This method is based on the hash code, for searching a similarity of learning hashing functions in multi-model data for cross view similarity and novel hashing method which referred to called matrix factorization hashing (CMFH). It learns unified hash codes by collective matrix factorization [7]. Hashing based similarity of method can view a all based on category or cluster format. The word representations are learned by recurrent neural network language mode. A word embedding is a representation of words as continuous vector, for that for a particular word a particular hash code will generate.

The processing flow of the proposed semantic cross-media hashing (SCMH) method is illustrated in Fig.2. In that we give a collection of text and images. First we represent a image and text respectively, for representing text a text are transformed to distributed vectors by the word embedding learning methods. And for representing images we use a SIFT detector to extract image key points. After these steps a fisher vector will generate for a particular word and particular descriptor. For that vector a hash code will generate and text and images are represented by vectors with fixes length. Finally, the mapping functions between textual and visual fisher vector (FVs) are learned by a deep neural network. We used a learned mapping function to convert FVs of one modality to another [8]. Hash code generation methods are used to transfer FVs of different modalities to short length binary vector.

II. LITERATURE SURVEY

In 2010, Yann Lecun et.al has conducted a study for learning good features for understanding video data. For that purpose they introduced a model that learns latent representations of image sequences from pairs of successive images and convolutional gated RBM and showed that it learned to represent optical flow and performed image analogies [9].

In 2011, Yuncho Gong et.al has conducted a study for learning similarity preserving binary codes for efficient retrieval in large scale image collections is the main problem for solving a that problem , has proposed a simple and efficient alternating minimization scheme for finding ration of zero centered data[10].

In 2011, Shaishav Kumar et.al has conducted many applications in multilingual and multimodal information access high dimensional data objects with multiple views. In this he considered as the problem of learning hash functions for similarity search across the views for applications for that purpose he proposed a principled method for learning a hash function for each data objects and formulated the learning problem as a NP hard minimization problem and that will be transformed into a tractable eigenvalue problem by means a novel relaxation [11].

In 2012, Zhen et.al has conducted both searches i.e. hashing-based similarity search and multimodal similarity search. In this hashing based similarity search seeks a scalability issue for address, and a multimodal similarity will deals with application in that application modalities of data are available. For this purpose he proposed a probabilistic modal, called as multimodal latent binary embedding (MLBE) this model has been conducted using both synthetic and realistic data sets [12].

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III. PROBLEM DEFINITION

The main problem is, most of the works uses a bag-of-words to model textual information. The semantic level similarities between words or documents are rarely considered and focused only on textual information. And another challenge in this task is how to determine the correlation between multi-modalrepresentations..

IV. ARCHITECTURE

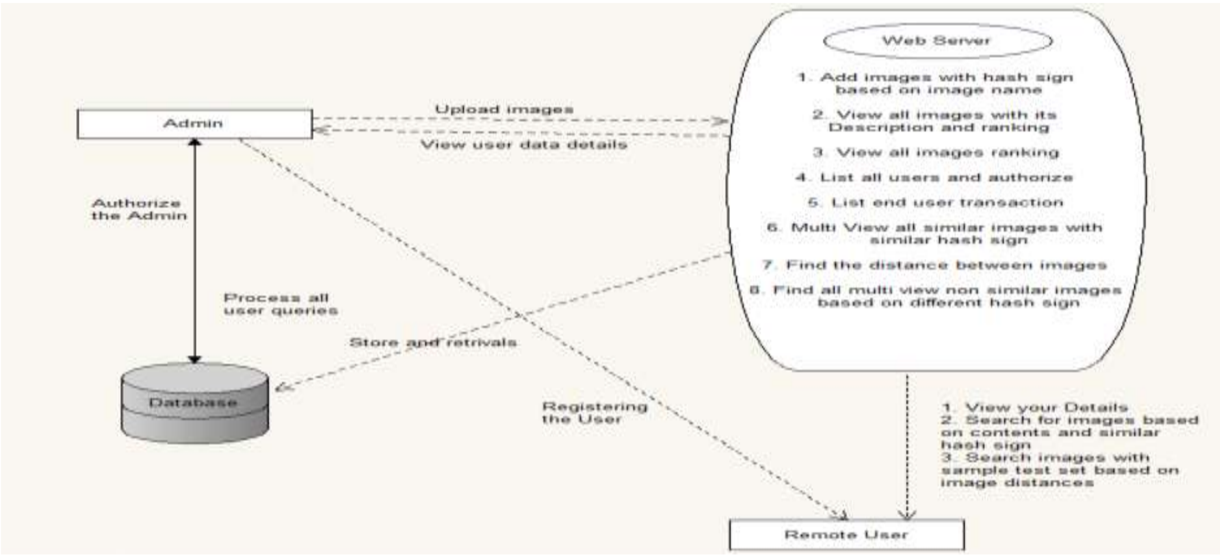

Fig 1: Architecture

In Fig. 1 An admin will authorize a new user and he can view all authorizes and users, he can add or upload a images even he can view all added images and similar and different image hash signs.And admin also find or view a distance between image, top retrieval image, mixed and user transactions and also he can view all images ranking.

A user will register first after resisting a user admin has to authorize that new user after authorizing, a new user can login, he can view his own profile and details. User can search a images based on content type and image type, and even he can search a transaction and image distance.

V. IMPLEMENTATION

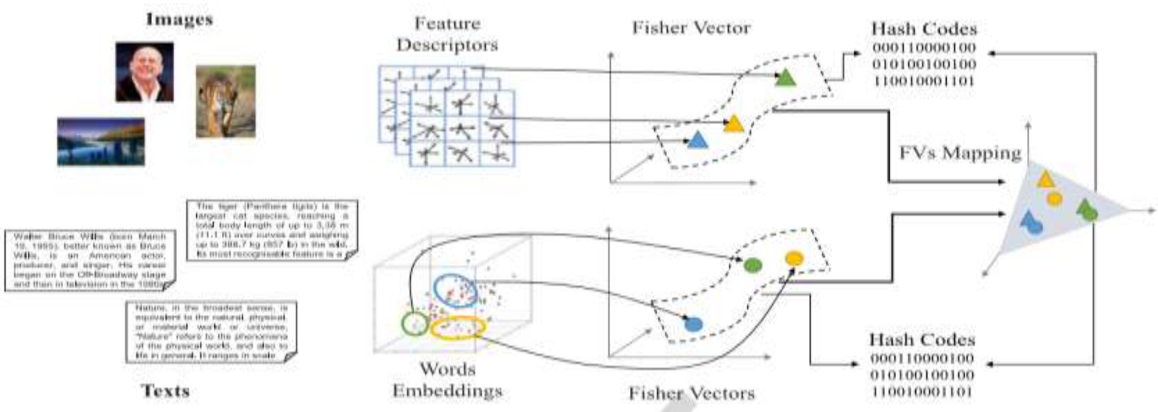

Fig 2: An overview processing flow of the proposed SCMH for cross-media retrieval

In this Mixed Generative-Discriminative Based Hashing Method, we are using a SHA1 algorithm (Secure Hashing Algorithm). This algorithm is mainly used to generate a hash code or message authentication code (MAC). This hashing algorithm is using for searching the post. For example, if we are searching one post in that two types are there one is content type and second one is image type for these two types a hash code will generate for a particular image but in this one more important thing is a content type is based on description and image type is based on title or

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name. The above fig. 2 shows a one of the best example for generating a hash code.

VI. RESULT

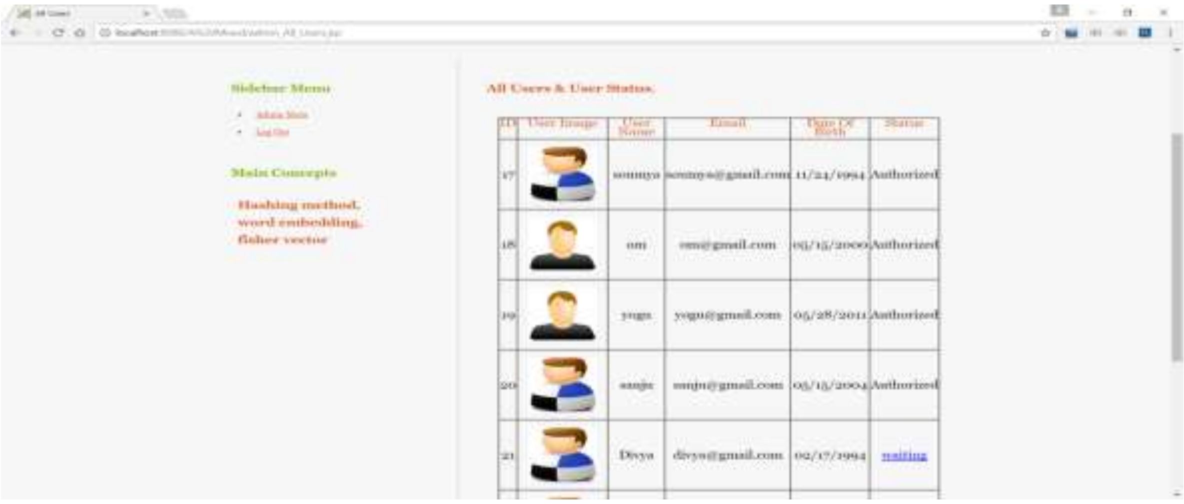

Fig 3: View all users and authorize

In Fig.3 Admin can view all users and he can authorize a user, and user has to register first before authorized by admin.

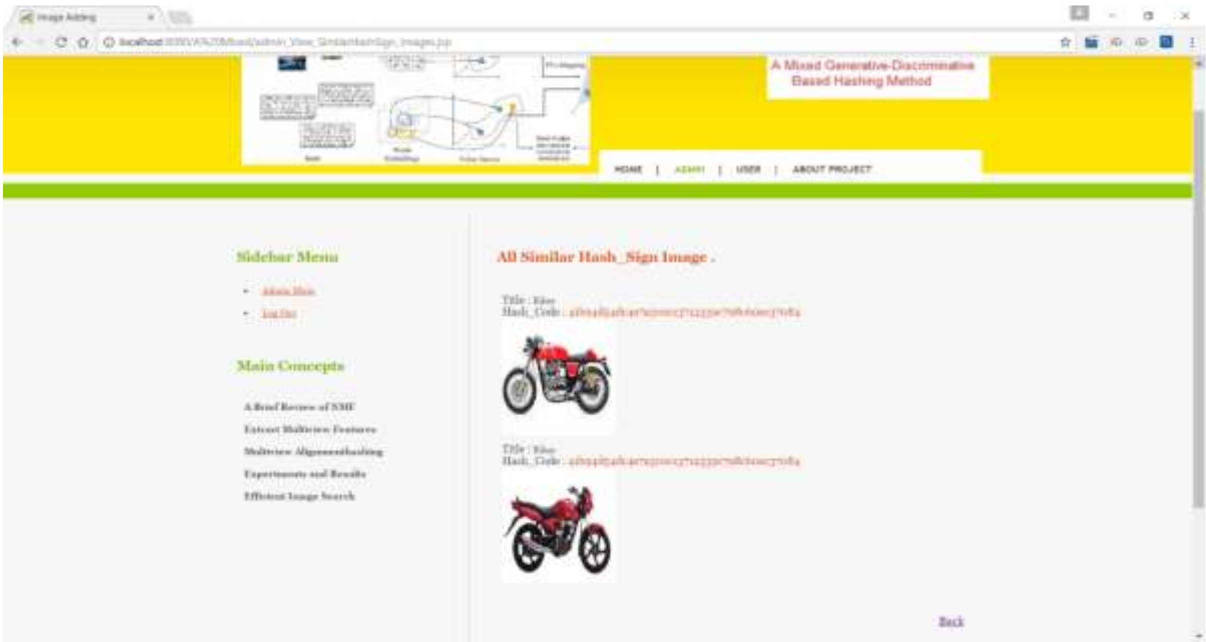

Fig 4: View all similar hash sign

In Fig.4 After searching the image a hash code will be generate for a particular image, in that admin can view all similar hash sign images.

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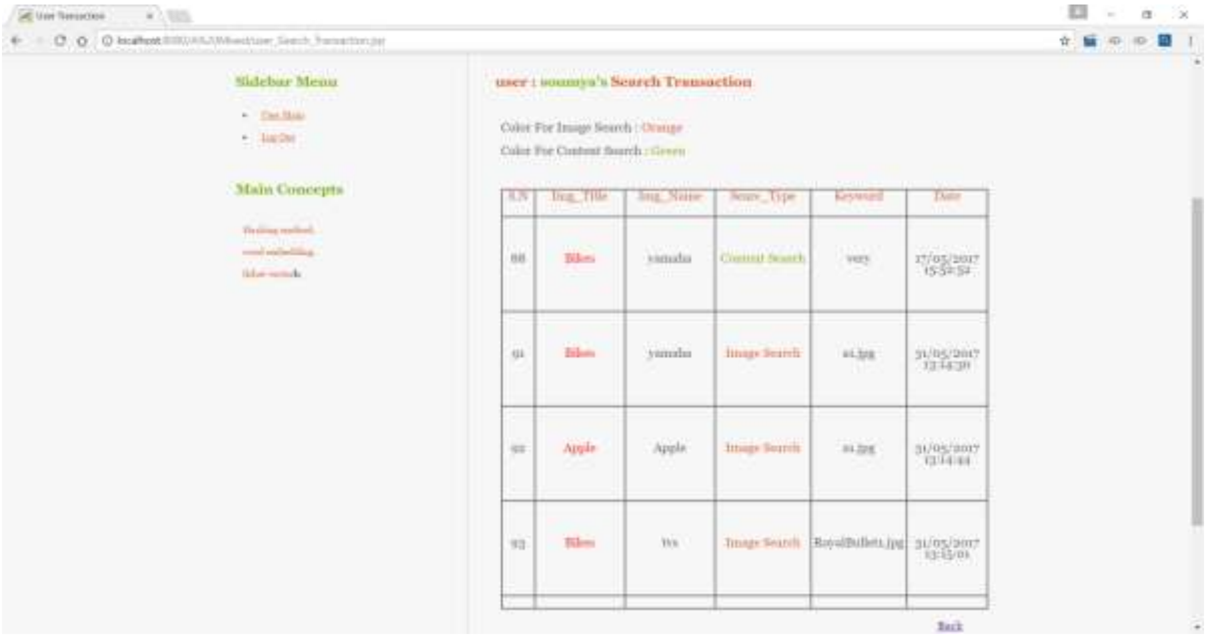

Fig 5: User Search Transaction

In Fig.5 User Transaction page will display searched images based on types like image and content search.

Fig 6: View rank details

In Fig.6 Admin can view all images rank details.

VII. CONCLUSION

In this work we have designed hashing method to perform SCMH, cross media retrieval task. We have proposed to use a set of word embedding's to represent textual and visual information with fixed length vectors. For mapping the fisher vectors of different modalities, a deep belief network is proposed to perform the task. We evaluate the proposed method SCMH on three used data sets. SCMH achieves better results than state-of-the-art methods with different lengths of hash code.

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