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MapReduce Neural Network Framework for Efficient Content Based Image Retrieval from Large Datasets in the Cloud

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***Abstract*—Recently, content based image retrieval (CBIR) has gained active research focus due to wide applications such as crime prevention, medicine, historical research and digital libraries. With digital explosion, image collections in databases in distributed locations over the Internet pose a challenge to retrieve images that are relevant to user queries efficiently and accurately. It becomes increasingly important to develop new CBIR techniques that are effective and scalable for real-time processing of very large image collections. To address this, the paper proposes a novel MapReduce neural network framework for CBIR from large data collection in a cloud environment. We adopt natural language queries that use a fuzzy approach to classify the colour images based on their content and apply Map and Reduce functions that can operate in cloud clusters for arriving at accurate results in real-time. Preliminary experimental results for classifying and retrieving images from large data sets were quite convincing to carry out further experimental evaluations.**

Keywords-CBIR; image retrieval, neural network, MapReduce, cloud

I. INTRODUCTION

Content-based image retrieval (CBIR) is a technique that involves retrieving specific images from image databases primarily based on features that could be automatically derived [1]. Typically, primitive features such as colour, texture, object or shape are used, and could be combined with logical features such as the identity of the objects in the image, or even abstract attributes such as the significance or relevance of the image within a context [2]. With the rising popularity of social media and the prevalence of mobile image capturing devices, the amount of images available in the digital media and databases has grown at an exponential rate [3][4]. Current CBIR systems are not capable of catering to high level user demands that are based on natural language queries, and the existing low level retrieval techniques adopted, based on colour, texture, shape and object, are highly inefficient with the exponential growth of large datasets.

Image databases could contain satellite pictures, art, engineering or scientific models and images in other forms including those used in medical, entertainment, and sports fields [5][6]. There is always a need to find a specific image from a large collection that could be shared by many professional groups or even available freely in the Internet. Searching for relevant content in large collections of image databases has become a difficult process [2][3]. Traditionally, such CBIR is mostly limited through a search using tags or keywords assigned with the image while storing in the databases. However, if the image is not uniquely tagged or described wrongly, the search results obtained will be of little value to the users. Hence, for accurate results, most of the CBIR systems use query images as examples for matching and retrieving the desired image from a digital collection [3][4][7]. In most of the situations, query images may not be available for the search, and users are looking for flexible and intuitive ways of image retrieval [8][9]. In addition, current CBIR techniques are computationally intensive for achieving high accuracies, and hence they are inefficient for real-time image retrieval from very large databases.

This paper proposes a novel CBIR technique of using natural language queries to retrieve images more accurately and efficiently, by adopting a MapReduce neural network framework for processing from very large image databases available in today's cloud environment. This technique overcomes the limitations of current CBIR systems that can operate only at the primitive feature level as users are given freedom to pose their queries in terms of natural language [10][11][12]. We combine image colours such as red, blue and green, and content types such as low, medium, high and very high in natural language queries. Our proposed technique performs fusion of such queries using neural networks. The computational intensive processing that could drastically slow down the search performance for a large media collection is overcome by parallelising using MapReduce framework [13]. The parallelism is achieved by splitting the process into many smaller sets of independent tasks and the concept of neural network ensemble (NNE) has been used to implement the fusion of classes that are formed based on colour and content specified by users in the form of natural language queries. Since Neural Network Ensembles (NNE) divide the data into smaller areas for faster learning of each class, it is more efficient than single neural network for processing large amount of data and therefore is a suitable candidate for applying the MapReduce framework such as Hadoop [14] to speed up the calculations and return the search results at a shorter time. The performance improvements gained from computing the process in a parallel manner within the MapReduce framework results in real-time efficiency even when scaled to very large image collections occupying petabytes of storage in the cloud.

The rest of paper is organized as follows. Section 2 provides a literature review of CBIR systems. Section 3 describes the proposed CBIR technique in a novel MapReduce neural network framework for large image databases. Section 4 presents the experimental results of our CBIR technique. Finally, conclusions and future work of this research are given in section 5.

II. Review of CBIR Systems

CBIR systems developed earlier such as QBIC [15], Virage [16], Photobook [17] and Netra [18] have used a weighted linear method to combine similarity measurements of different feature classes. However, more sophisticated techniques have recently been introduced.

The main motivation for the development of this system is that region-based search improves the quality of the image retrieval. Therefore the system incorporates an automated region identification algorithm. There are other existing techniques in the literature for content-based retrieval such as satellite image browsing using automatic semantic categorization [19], partial relevance in interactive facial image retrieval [20] and region-based image clustering and retrieval using multiple instance learning [21]. A detailed survey published in 2005 on content-based image retrieval can be found in [22].

Computational intelligence based techniques such as neural networks have also been applied by some researchers to develop a prototype for CBIR. Neural networks have also been proposed for feature extraction [23], similarity measurement [24], relevance feedback technique [25]. Images are compared through a weighted dissimilarity function which can be replaced as a "network of dissimilarities." The weights are updated via an error back-propagation algorithm using the user's annotations of the successive set of the result images [26]. It allows an iterative refinement of the search through a simple interactive process. Not much work has been done in the area of fuzzy logic based linguistic queries for image retrieval. Fuzzy logic has impressive power to represent the queries in terms of natural content of the image.

In [27] an image is represented by a set of segmented regions each of which is characterised by a fuzzy feature reflecting colour, texture and shape properties. The resemblance between two images is then defined as the overall similarity between two families of fuzzy features and quantified by unified feature matching. Non-Boolean fuzzy and similarity predicates are used to rank tuples according to fuzzy based algebra [10]. Soft queries in image retrieval systems present the use of soft computing and user defined classifications in multimedia database systems for content based queries [28]. A CBIR system which automatically clusters images using features of those images which are fuzzy in nature. Image is described on a fuzzy rule based compact composite descriptor which includes global image features combining brightness and texture characteristics [29]. Paper presented by Yu and Dunham [30] proposed fuzzy logic based method to automatically generate the description of spatial relationship among objects and graph based fuzzy linguistic metadata schema for topology and relationship for a set of objects.

In [31], fuzzy logic is imported into image retrieval phase to deal with the vagueness and ambiguity of human judgment of image similarity by adopting the fuzzy language variables to describe the similarity degree of image features, not the features themselves. The fuzzy inference is then used to instruct the weight assignments among various image features. In [32] paper presents a fuzzy-neural approach for interpretation and fusion of colour and texture features for CBIR systems. Similarly, a novel fuzzy approach is proposed to classify the colour images based on their content, and to pose a query in terms of natural language for fast and efficient retrieval [33]. In this paper, we advance such an approach further by proposing a MapReduce neural network framework for a real-time efficient CBIR system that can process petabytes of data from very large image databases. We make use of cloud clusters for introducing parallel processing to achieve the desired accuracy and time efficiency that is warranted in real-life applications of CBIR.

III. Proposed MapReduce Neural Network Framework for CBIR

A. *What is MapReduce?*

MapReduce is a distributed computing framework to support parallel computations over large datasets in multiple petabytes of storage available on clusters of computers. The framework also has the advantage of parallel processing of such Big Data on large clusters of commodity hardware in a reliable, fault-tolerant manner.

The concept originates from map and reduce functions commonly used in functional programming like Lisp, and have been improvised in MapReduce framework, which transform a list of pairs <key, value> into a list of values. The Map functions are invoked in a distributed environment across multiple machines by automatically partitioning the input data into a set of K splits. These partitioned input sets can be processed in parallel on different machines. Reduce functions are invoked in a distributed environment by partitioning the intermediate key space into P pieces using a partitioning function such as a hashing function, hash(key) mod P.

The MapReduce framework consists of a single master Job Tracker and one slave Task Tracker per cluster node. The master is responsible for scheduling the jobs' component tasks on the slaves, monitoring them and re-executing the failed tasks.. This way reliability and fault tolerance is taken care of. Figure 1 shows an example of high level architecture of the MapReduce Framework implemented in Hadoop with a cluster setup consisting of 1 master node and 2 slave nodes. Image files and their extracted features are stored in the DataNodes by utilizing Hadoop Data File System (HDFS). This would facilitate batch processing of the files and features during MapReduce search tasks that are assigned by the job tracker to the task tracker present in each of the nodes to facilitate parallel processing in a cluster environment.

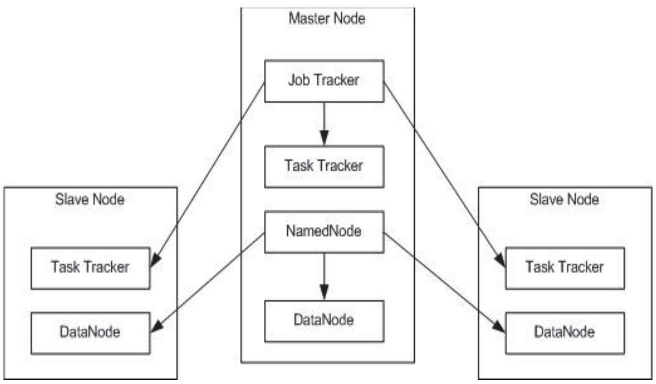

Figure 1. Architecture of a Cluster Setup for MapReduce

B. *Neural Network Ensembles for CBIR*

The shortcomings and problems encountered with traditional methods of image retrieval have led to the rise of interest in CBIR techniques. At present there are some commercial products like QBIC [15], Virage [16], Photobook [17] and Netra [18]. As mentioned earlier, they combine similarity measurements of different feature classes using a weighted linear method. Such techniques lack high level processing as they are not sophisticated enough to handle real life multiple natural language queries from users [32][33][34], and more importantly in efficiently searching from very large and diverse image datasets. To address these limitations, we have adopted a hybrid technique for CBIR based on fuzzy logic and neural networks within a MapReduce distributed framework for processing very large image collections in the cloud.

In this proposed framework, natural language queries posed by the user are processed in parallel to retrieve relevant images from large data collections. . We combine the colour features such as Red, Orange, Yellow, Green, Cyan, Blue, Purple, Magenta, Pink, Black, White and Grey, as well as fuzzy terms of colour content such as 'no colour', 'very low', 'low', 'medium', 'high', and 'very high' for colour image classification and perform retrieval using neural networks. This involves steps which include fuzzy interpretation of user queries, neural network to train the queries and a technique for the fusion of multiple queries.

The most important step of training the classes for the fusion of queries facilitates in accuracy of results and we adopt a neural network based technique for this purpose. We adopt supervised learning neural network to efficiently learn the colours and content types and a neural network ensembles (NNE) for the fusion of classes. In situations that require processing of large image datasets, NNE is produces more accurate outcomes as they are robust and efficient than single neural network.

The advantage of NNE is that different networks such as multilayer perceptrons, radial basis functions neural networks, and probabilistic neural networks, can take as inputs samples characterised by different feature of colour and content type. Feature set F_M for the colour Magenta in an image is given by the following formula:

$$F_M = \frac{N_M}{N_P}$$

where, N_M represents the number of magenta colour pixels in the image. and N_P represents the total number of pixels in the image. Figure 2 shows a typical NNE, where separate neural networks are formed for each of the colours from Red to Grey and the content types ranging from very low to very high. Here, we introduce parallel learning of neural network tree ensembles with MapReduce.

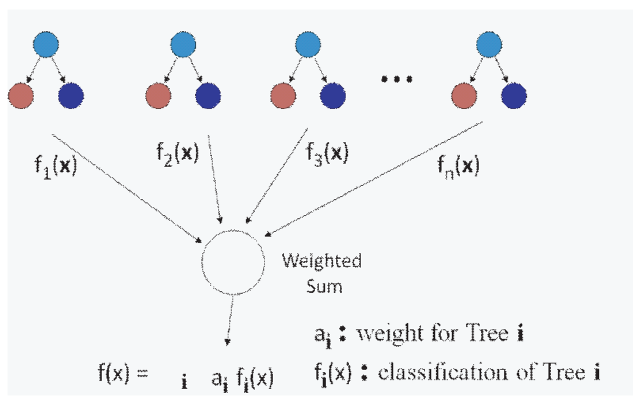

Figure 2. Neural Network Ensemble for Image Classification

C. *MapReduce Neural Network Implementation*

The parallel framework offered by MapReduce is highly suitable for the neural network ensemble technique of our proposed CBIR framework. It can perform efficient data-intensive computations and machine learning for image classification and retrieval from very large digital image collections. We describe the implementation details of MapReduce in this section.

MapReduce uses two functions called Map and Reduce that process list of pairs <key, value>. The Map function inputs a list input key and associated values and produces a list of intermediate <key, value> pairs. For CBIR, the image features represent the keys and image files as values. Next, grouping and shuffling of intermediate pairs with same keys are performed. The Reduce function then does the merge operation on all intermediate pairs for the same key and outputs the results. Here the Reduce function can be executed in parallel. An illustration of the MapReduce implementation for our proposed CBIR framework is shown in Figure 3. For images, the process is illustrated as follows

$$\text{Map: } < Feature1, \text{File1} > \rightarrow \text{ List} < Feature2, \text{File2} >$$

$$\text{Reduce: } < Feature2, \text{List} < File2 >> \rightarrow \text{ List} < Feature3, \text{File3} >$$

The neural network ensemble is applied into a two-stage MapReduce process, with one for training the classifier and the other for validating the classifier. All the input pairs, outputs pairs and intermediate pairs are stored in the Hadoop Distributed File System (HDFS) as it provides a large-scale data storage infrastructure based on clusters in the cloud. As shown in Figure 1, the overall scheduling and running of the MapReduce jobs are managed by the Hadoop with a job tracker in a master node that assigns tasks to slave node and each task would consist of multiple Map and Reduce functions. It takes care of balancing the tasks and optimising the overall runtime, making our proposed CBIR real-time efficient for processing very large image datasets.

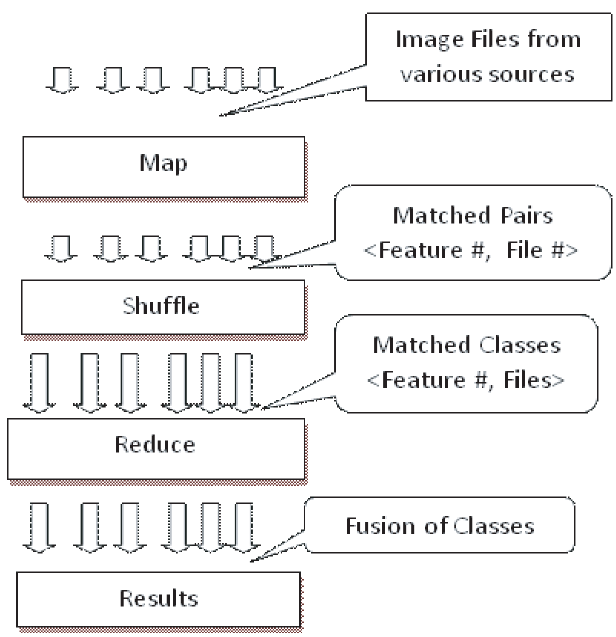

Figure 3. Illustration of MapReduce Implementation for CBIR

IV. Experimental Results and Future Work

The experiment conducted consists of five main stages and a preliminary testing of our proposed CBIR technique was conducted using an image dataset of about thousand images collected from public domains. We included images of different categories such that different colours and hues were covered to a great extent and all the content types were included in the evaluation. Some of the categories used for testing included images of babies, beaches, birds, boats, cars, dogs, fireworks, flowers, landmarks, nature, planes, planets, sunsets, waterfalls and weddings, etc. The following five stages were performed in our CBIR .

Stage 1: Feature Extraction - Here the RGB and HSV values were combined to determine colours (Red, Orange, Yellow, Green, Cyan, Blue, Purple, Magenta, Pink, Black, White and Grey). Colour pixels were extracted and for each pixel the colour ranges were determined. We calculated the colour content by incrementing the relevant colour counter when the relevant colour pixel was found and the total for the entire colours were also calculated to estimate the percentage of each colour.

Stage 2: Feature Storage using MapReduce - Features extracted in Stage 1 were stored in text files for each image. These are in the form of pairs <Feature#, File#> of the Map function of the MapReduce framework.

Stage 3: Natural Language Query - The user query could have a combination of colours from the set {red, orange, yellow, green, cyan, blue, purple, magenta, pink} and content type in natural language terms from the set {no colour, very low, low, medium, high, very high}. This way user need not pose a similar image for the query. An example output of the features of the experiment with natural language query, where we can see the main colours as magenta, pink, purple and black is shown in Figure 4.

Image	Colour	%	Fuzzy Logic Terms
	Red	0.35	No Colour
	Orange	0.02	No Colour
	Yellow	0.01	No Colour
	Green	0.01	No Colour
	Cyan	0.01	No Colour
	Blue	1.16	Very Low
	Purple	36.93	Medium
	Magenta	24.38	Low
	Pink	29.06	Medium
	Black	5.4	Very Low
	White	2.65	Very Low
	Grey	0.04	No Colour

Figure 4. Features extracted using natural language query

Stage 4: Image Classification using MapReduce - In this stage the image is classified based on the fuzzy logic membership function. We used the following fuzzy classes for colour contents for each image: very low [0.05, 0.1], low [0.11, 0.35], medium [0.36, 0.65], high [0.66, 0.80], very high [0.81, 1.0]. A neural network ensemble (NNE) based fusion of classes are done and the image classification is done using the Reduce function of the MapReduce framework.

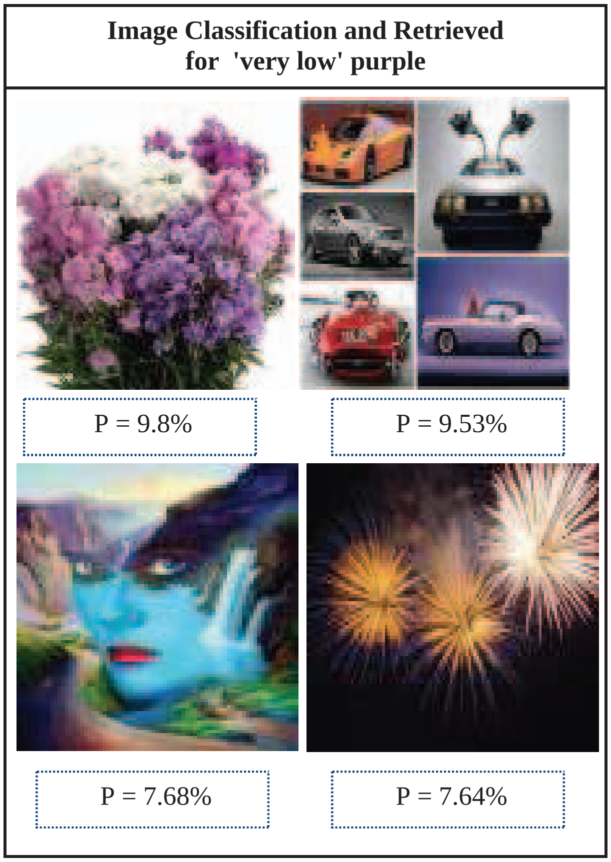

Figure 5. Image retrieval results for user query 'very low' purple

Stage 5: Retrieval and Indexing - In this stage, the user query is used to match with the images in the data set using neural networks for the classification and indexed based on percentage of colour relevance. The classified images are retrieved and are displayed in descending order of colour relevance. Figure 5 provides a list of images retrieved when the user query was very low purple in descending order of percentage relevance (P) values.

The preliminary results are quite promising for single dataset collection of images and future work would involve testing with very large data sets stored in multiple cloud clusters and evaluating the speed of processing. Though parallel processing would reduce the speed to a great extent, the additional overhead of pooling results from the distributed clusters has to be considered. There would be a threshold number of cloud clusters beyond which parallelism would not be beneficial. These thresholds will also be evaluated in our future work.

V. Conclusions

Thousands of images are added to image database and Internet everyday for the applications in health, security, arts etc. Due to adavances in technology such as cloud computing, it is very important to retrieve the images effectively and efficiently stored at various locations. This paper evaluates various CBIR systems developed using conventional as well as computational intelligence techniques and proposes a novel MapReduce Neural Network framework for CBIR in five stages. Fuzzy logic is proposed for posing natural languagae query in terms of content of an image and neural network is proposed for classification of images according to fuzzy content. Preliminary results are demonstrated in the paper along with analysis of results.

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