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A Novel Model for Visual Content Based Image Retrieval using Transfer Learning

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Abstract: ***At present, the revolution brought by deep learning based technologies in the field of computer vision gaining momentum in the world of artificial intelligence. In particular, the best models for retrieving common images today are based on features generated by deep convolutional neural networks (DCNNs). However, this great success was expensive. A comprehensive amount of tagged data had to be collected, followed by model design and training. Meanwhile, a transfer-of-learning approach has been developed that avoids this costly step by applying a sophisticated, pre-trained generic DCNN model to completely different data domains. With the use of transfer learning, it becomes possible to use deep CNN models for small datasets with better retrieval performance with respect to handcrafted feature based retrieval methods. In this paper a deep CNN based model has been proposed which uses concept of transfer learning and achieves good classification accuracy.***

Keywords: ***Deep Convolutional Neural Network, Transfer Learning, Pre-trained Networks, Visual content based Image Search and Retrieval***

I. INTRODUCTION

With the advancement of AI enabled technology in every field of today's world, the term 'Social Media' becomes so popular that a large percentage of population remains interconnected 24 x 7 through various devices. This interconnection of the devices generates large volume of data continuously as text, image or video. To store, process and extract information from these sources of data can be a challenging task and needs attention from scientists, academicians, researchers, data analysts etc. The success of deep CNNs (Robinson & Yun, 2016) lies in the utilization of GPUs, Relu's, data augmentation and in adding new drop out layers for regularization [14]. The different CNN architectures have the capability to extract discriminating feature set at multiple levels of granularities. Any CNN trained from scratch requires huge volume of labeled dataset, huge storage requirement and convergence issues with learning parameters. To overcome these limitations, the concept of transfer learning is very much popular these days for the problem of visual content based image search and retrieval [11, 12].

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When a CNN model developed for a task can be reused for another task with improved learning rate through transfer of learned parameters on large volume of dataset during first task, it will be called as pre-trained network. A DCNN model can be trained on any large publically available database for learning generic features of an image. Then this CNNmodels utilizes model parameters found for large dataset to fine tune with the target and small dataset for learning semantically higher visual features of an image. This process of fine tuning of parameters helps to extract specific features for better adaptation of the targeted task. The pre-trained networks can be used as high dimensional feature generators on small datasets. The high dimensional feature sets may cause problem of over fitting and can be solved with the use of dimensionality reduction techniques such as PCA, SVD, Sparse Coding or by introducing global average pooling layer [1]. Different classification techniques such as SVM, Decision Trees or Random forest can be used for accurate classification of image features for taking as input for similarity measurement step during visual content based image retrieval [13], [15], [16].

II. LITERATURE REVIEW

A CNN model using sparse coding method to reduce over fitting during dimensionality reduction step for scene classification problem was proposed on a large volume of remote sensing image dataset [1]. The deep features extracted using various feature maps was converted into low level sparse coding features and with the help of various pooling methods, These features were concatenated to form a feature vector for getting global features for classification. The proposed algorithm was compared with PCA and global average pooling (GAP) based methods used at fully connected layer of any pre-trained CNN model and was found efficient and accurate with 93.64% accuracy rate. In paper [2], A CNN model for defect pattern classification on wafer bin maps (WBM) of semiconductors was developed for improving classification accuracy on a small dataset in very small time. The authors have used WM-811K dataset for validation and only 1400 data elements for CNN to get classification accuracy around 98.44%. The author's states that different companies in the semiconductor industry can use their CNN based retrieval and classification model for analyzing defect patterns in semiconductors within very short time. A review on tyre pattern image retrieval (TPIR) was conducted in paper [3] realizing an urgent need of TPIR system to help in investigations done by traffic police on road accidents.

The conclusions from the review can be states as lack of large public tyre image dataset, need of deep learning based methods for improving resolutions of accidental tyre images and the use of hybrid CNN models for enhancing the accuracy and efficiency of tyre pattern image retrieval systems. In paper [4], Inception V3 pre-trained model was used to extract low level visual features from the last layer of the model of an image. These lower level visual features were categorized into different classes then again feature extraction process was repeated for each class to get single feature vector by combining all features. The authors have used CUB200-2011 bird image dataset and got 99.46% training accuracy and 84.56% validation accuracy. They have improves validation accuracy upto 88.89% by using 3 branched global descriptors using MS-RMAC feature extraction method. The authors of paper [5] develop a trade-mark logo image retrieval system based on fine-tuned CNN model. They have used concept of transfer learning to fine tune additional layers of the CNN model on logo-2K+ dataset. The authors have designed a triplet loss function to get better differentiation between company logos and their infringements by cyber criminals. The prototype 'LogoSimNet' was developed for getting efficiency, consistency and accuracy enhancement during trade mark logo image retrieval and verification process. The paper [6] proposed a novel CNN based wool fabric retrieval method to get diffentiation based on appearance using hand crafted features and parameters of pre-trained models with the help of transfer learning concept. Oriented FAST and related BRIEF (ORB) was used as feature extractors to generate feature database. The Ball Tree method was used to search nearest or similar retrieved images automatically.

An ensemble of deep neural network model for foot print image retrieval [7], A CBIR method for dose distributions of previously planned patients based on anatomical similarity [8], A CNN model for medical image retrieval using transfer learning [9] and a framework with fusion of feature with transfer learning retrieval algorithm [10] were proposed by different researchers in the field of visual content based image retrieval.

III. RESEARCH METHODOLOGY

The visual content based image retrieval can be considered as a two-step process-Feature Extraction process, and similarity measurement and image indexing process. The first process consists of two sub steps as training pre-trained networks (VGG19, ResNet50, and Squeeze Net) on Image Net dataset and generates combined feature vector consisting of all features from these pre-trained networks. This feature vector contains high dimensional features which require dimensionality reduction (Global Average Pooling (GAP)) technique to overcome with the problem of over fitting. Resulted features are then selected based on class labels and these networks are trained on ImageNet dataset. After this training step, proposed deep CNN model using the learned training parameters is applied on selected natural scene dataset for extracting features followed by dimensionality reduction and feature selection step. Euclidian distance is used as similarity parameter to find relevant images as per the query image from the database image [14]. All retrieved images are being sorted in order to do the indexing of the images. Top 10 best matches will be displayed as a result of the retrieval process.

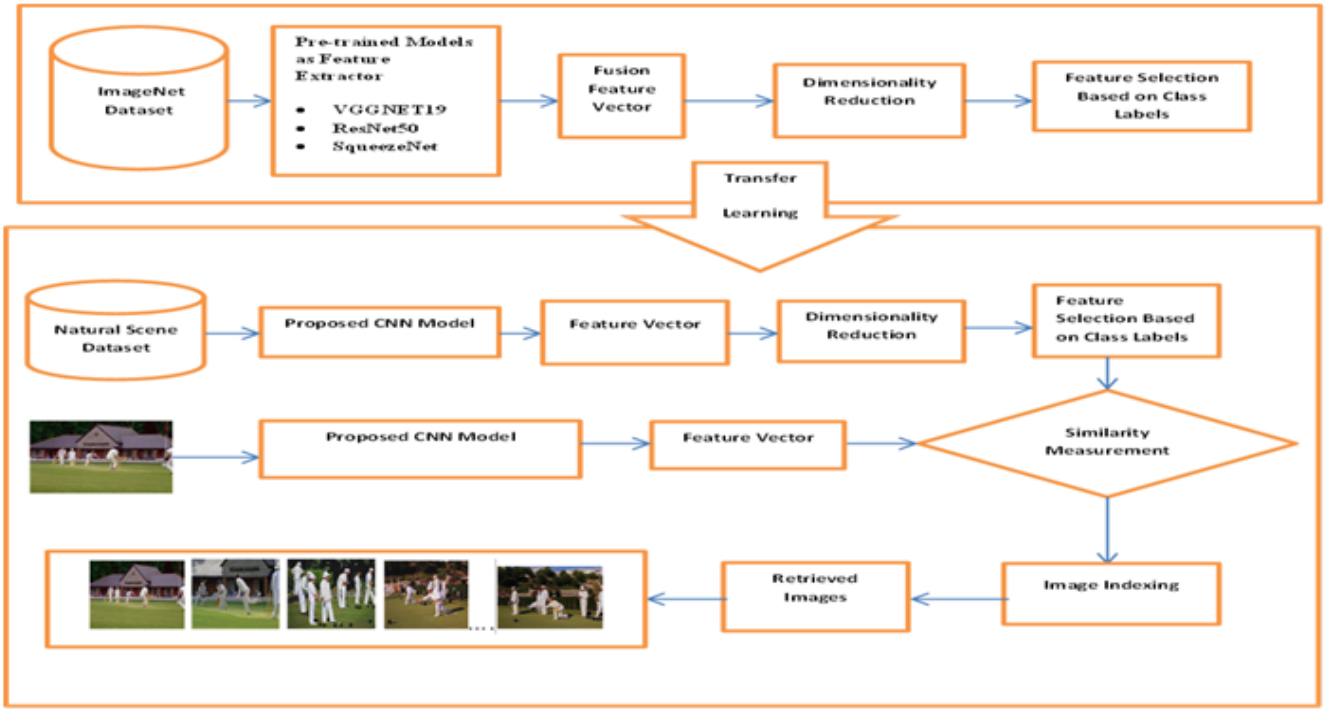

Figure 1. Research Methodology

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A. Proposed Deep CNN Model

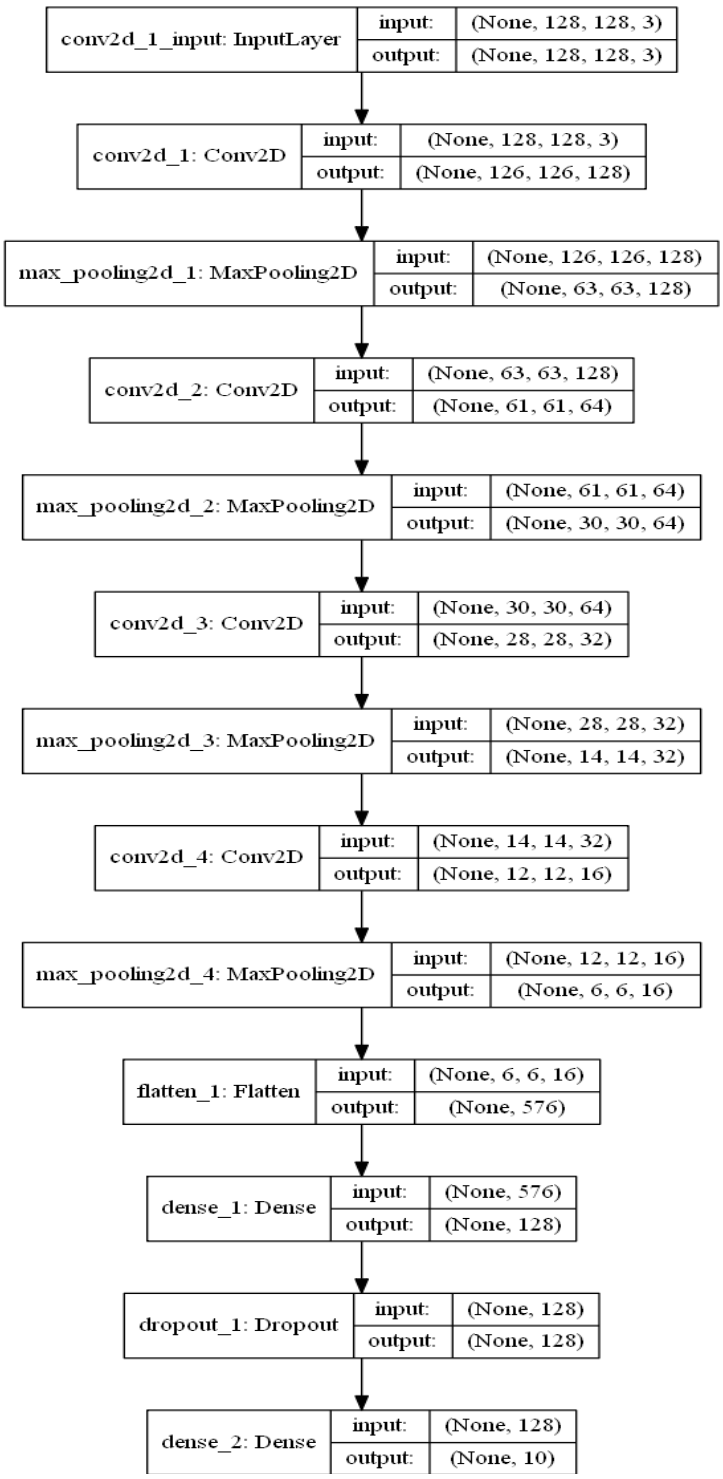

Figure 2. Proposed DCNN Model

In this paper, a novel DCNN model has been proposed to use learned parameter values from three different pre-trained CNN models for retrieving images based on automatic deep features extracted from the chosen natural scene dataset. The proposed model has been used to do the feature extraction followed by dimensionality reduction step by adding global average pooling (GAP) layer to classify deep features into 20 different classes, each having multiple features of around 2000 images. The model takes input RGB images with resolution 128x128x3 in the form of a matrix with 3x3 size filters.

Total 128 filters at the convolutional layer and max pooling layer with 2x2 pool size has been used in a single block. Both convolution and pooling operation has been repeated 3 times with different filter sizes having each filter of 3x3 and pool size as 2x2. At least, global average pooling(GAP) layer has been added to perform dimension reduction of deep features.

The hyper parameters of the proposed DCNN are shown as in the following table.

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Table 1: Learning Parameters of proposed DCNN model

Hyper-parameter name	Value
Training Epochs	250- 750
Train/Test Batch Size	64
Validation steps	100
Dropout Value	0.5
Learning Rate	0.0001
Dataset size	20000
Validation Set Size	4000

B. Pre-trained Networks for Feature Extraction:

As per the review of literature done on deep learning based image retrieval systems, it has been found that out of different pre-trained CNN models used in the image retrieval problems, the best three pre-trained models based on accuracy are VGG19, ResNet50 and Squeeze Net on Image Net Dataset[17], [18] ,[19], [20]. So, these models has been considered to perform fusion of deep features and they has been trained on the Image Net dataset to use their learned parameters in the proposed DCNN model to get better performance of image retrieval. The architectures pf all three pre-trained models have been shown below.

1. VGG19

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

2. ResNet50

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

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3. Squeeze Net

layer name/type	output size	filter size / stride (if not a fire layer)	depth	s_{1x1} (#1x1 squeeze)	e_{1x1} (#1x1 expand)	e_{3x3} (#3x3 expand)	s_{1x1} sparsity	e_{1x1} sparsity	e_{3x3} sparsity	# bits	#parameter before pruning	#parameter after pruning
input image	224x224x3										-	-
conv1	111x111x96	7x7/2 (x96)	1				100% (7x7)			6bit	14,208	14,208
maxpool1	55x55x96	3x3/2	0									
fire2	55x55x128		2	16	64	64	100%	100%	**33%**	6bit	11,920	5,746
fire3	55x55x128		2	16	64	64	100%	100%	**33%**	6bit	12,432	6,258
fire4	55x55x256		2	32	128	128	100%	100%	**33%**	6bit	45,344	20,646
maxpool4	27x27x256	3x3/2	0									
fire5	27x27x256		2	32	128	128	100%	100%	**33%**	6bit	49,440	24,742
fire6	27x27x384		2	48	192	192	100%	**50%**	**33%**	6bit	104,880	44,700
fire7	27x27x384		2	48	192	192	**50%**	100%	**33%**	6bit	111,024	46,236
fire8	27x27x512		2	64	256	256	100%	**50%**	**33%**	6bit	188,992	77,581
maxpool8	13x12x512	3x3/2	0									
fire9	13x13x512		2	64	256	256	**50%**	100%	**30%**	6bit	197,184	77,581
conv10	13x13x1000	1x1/1 (x1000)	1				**20%** (3x3)			6bit	513,000	103,400
avgpool10	1x1x1000	13x13/1	0									
	activations	parameters					compression info				1,248,424 (total)	**421,098** (total)

C. Experimental Setup

The proposed model has been implemented using different python libraries and packages used for different computer vision operations asScikit-Learn, Keras and Open CV. The machine NVIDIA DGX-1 V100 using 8X Tesla V100 GPUs with Performance of One peta FLOPS was used to run the coding of the retrieval system.The chosen dataset was segregated as training and testing datasets in the ration of 80:20. The classification results were demonstrated through the use of confusion matrix as shown below. The grids in green colours show the number of correctly classified images with respect to each row. Suppose the class labelled as horses, total 400 images has been given as input to the model for classification, 380 images has been found correct with the same label of the class as horses. Among 400 images, 5 images matches with class label as farms, 5 as bears, 10 as tigers and 5 as dogs. Hence the classification accuracy of the proposed model by considering only 10 classes is 95% for the horse class only. The overall classification accuracy for the proposed DCNN model is 96% taking average of all classes.For the calculation of accuracy with respect to each class, following formula has been used.

$$Accuracy = \frac{Total\ true\ positive\ samples}{Total\ number\ of\ samples} \quad (1)$$

IV. RESULTS AND DISCUSSION

To perform image retrieval based on deep features with the use of pre-trained models, many researchers have done experimentation and have found good results as per the available literature [13-20]. Very few studies can be found in the literature on the fusion of deep features with the use of pre-trained models by using the concept of transfer learning. The deep learning CNN model proposed in this paper for performing visual content based image retrieval achieves classification accuracy around 96% which is better the available state of art algorithms.

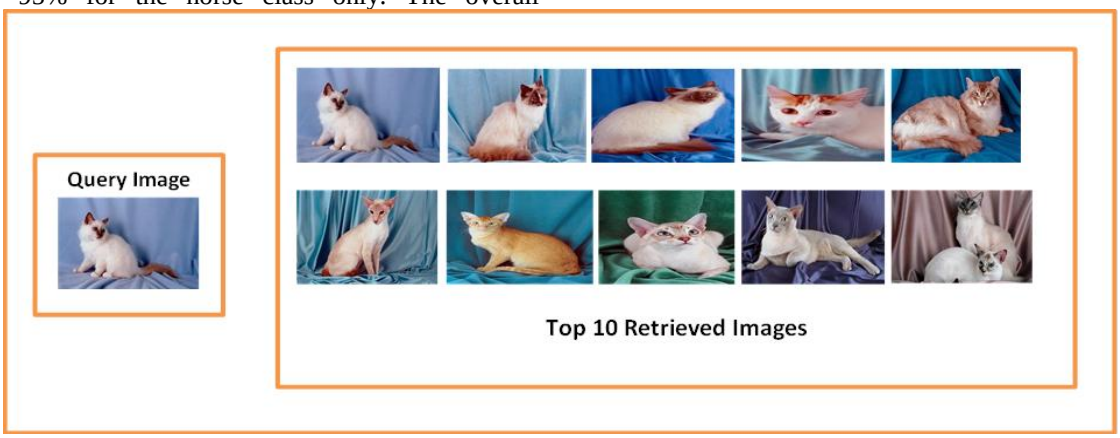

Figure 3. Top 10 Retrieved Images

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	Horses	Photography	Farms	Bears	Buses	Cars	Tigers	Cats	Dogs	Drinks
Horses	380			9					10	
Photography		375	8		10	15				
Farms		10	372							13
Bears	5			381			4	5		
Buses		10			370					5
Cars					10	385				
Tigers	10		10	10			388	10		
Cats		5					8	385	10	
Dogs	5								380	
Drinks			10		10					382
Classification Accuracy	95	95	93	95.25	92.5	96.25	97	96.25	95	95.5

Figure 4. Confusion Matrix for 10 Classes

V. CONCLUSION AND FUTURE WORK

Image retrieval with social media platforms and large databases becomes so much necessary and important for improving the use of social media contents through different devices that requires deep feature based new algorithms with better implementation and with very less time to process the query images. This paper attempts to do so by proposing a deep CNN based model and achieves good classification accuracy. In future, fusion with feature extraction algorithms, classification algorithms and image indexing algorithms can be proposed to improve accuracy and retrieval time for large databases.

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