Scene Recognition using Significant Feature Detection Technique

Priya Singla, Rajesh Mehra

Abstract: Scene classification is basic problem in robotics and computer vision application. In Scene classification focused on complete view or event that contains both low and high level features. The main purpose of scene classification is to diminish the semantic gap in between social life & computer system. The main issue in scene classification is recognizing tall buildings, mountain, open country and inside city. We applied combination algorithms of feature extraction on trained datasets. Our proposed algorithm is hybrid combination of SIFT+ HOG named as HFCNN. As compare with the existing CNN architecture, HFCNN perform betters with high accuracy rate. Accuracy rate for proposed architecture is more than 96% as calculated with better time consumption and cost effective.

Keyword: Scene classification, Multimillion images, Local & global feature, Image Net and Convolutional Neural Network.

I. INTRODUCTION

Scene Recollection is widely used in autonomous system, computer vision applications and robotics system. Scene, Object and image recognition have many similarities, but the only difference is when we are consternate only objects that is known as object recollection and when we focused on surrounding present in picture is known as scene recognition and when we explained the information that is present in image at that time it is known as image recollection[1]. Scene is a view of real time environment that contain many view in a meaningful manner like hospital room, railway station, airport waiting room, kitchen etc. If somebody talking about kitchen at that time in human brain automatically the scene of kitchen that is loaded with crockery and utensils is build up. Identify the correct object with respect to its surrounding is known as scene recollection [2,4].Two different types of scene present in environment:- first one is real time & second one is artificial environment. Nature scene lies under real time and indoor scene lies under artificial. Scene recollection mainly focused on object identification & low level image features. Picture look-alike has huge range of applications in real world such as scene identification, object identification. In addition image matching is the important/prior operation for retrieving the significance & meaningful information from an image[2]. Feature detector is fundamental factor used to brief the presence of an image batch.

Various typesof feature descriptor used in image processing like SIFT, HOG, FAST, BRISK & FREAK. All are havingdifferent kind of functionalities [5, 6]. Out of these descriptorsSIFT &HOG are basic and reliable method that is used for feature detection in scene recollection [1].

SIFT stands for scale invariant feature transform, promote us to discover & narrate features of scene. SIFT works as a feature detector as well as descriptor. SIFT basically used for local feature extraction. SIFT applies a sequence of difference of Gaussian filters for a couple of scales in this way we got filtered and down sampled variations of unique image[3]. It is composed of 4x4 array of gradient orientation. SIFT made from two components i.e. key-point detector & descriptor. Firstly detector finds out the point in a picture that re invariant to transform and after that descriptor is used to define the appearance of the surrounding region of key point [3, 7]. The scale space of picture is shown as-

$$p(a, b, \sigma) = g(a, b, \sigma) * j(a, b)$$

Where left side represents is scale space of a picture and on right side function of Gaussian with source picture.Finding some particular thing from an image is difficult task because the presence of many variables. For this purpose robust feature set needed that is permitted the person to be discriminated cleanly, in disordered state and hard illumination. These types of cases HOG descriptors performed very well because it works on local and global both feature extraction. HOG works on spreading the intensity gradients principle without removing the edge location information [8,9].

II. RELATED WORK

The recognition techniques build a semantic representation for reducing the semantic gap. The face recognition methods works on extracting the features from single resolution image. The redundant features of the single image resolution may reduce the accuracy of scene recognition.

Bolei Zhou et. al.in [1] proposed a research on repository 10 million image scene using the Convolutional Neural Networks approaches. The visualization of the CNN shows the object detectors for the classification of the scene image. In order to get the high coverage and diversity, the places Database along with the Places-CNNs offer a resource to for the problems of scene recognition. The multimillion datasets have machine learning algorithm to identify the objects and scenes images. **P. Espinace et.al. in [2]** have proposed a new approach for visual indoor scene classification using mobile robot technology.

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Proposed method following by three steps- firstly probabilistic hierarchical model is used for associate low level features to objects, secondly exploit the embedded nature of mobile robot by using 3d information to implement a focus of attention mechanism and last one is adaptive strategy used to searching relevant objects. This approach implemented on real information captured by a mobile automaton navigating in workplace and residential environments. The results indicate that the proposed approach output is better several state-of-the-art techniques for scene recognition. **Bolei Zhou et.al.in [3]** has presented different-2 data sets of images for scene recognition. He defined the brief description of construction steps of PLACES database. He has taken two different categories of datasets i.e. Places-CNN, ImageNet. CNN applied these datasets on CNN classifier + SVM. At the end compare the accuracy level of CNN architecture on given datasets that consists 7 million images and showed how hybrid CNN architecture gave best accuracy i.e. 52.4% as compare to state-of-art methods. **XiaoyongBian et.al.in [4]** author has given fusion method of Local & global features for Scene Classification. He proposed Saliency-based multiscale multi structure (SalM3 LBP) for global feature extraction and Codebook less Model (CLM) for local feature extraction and he states that his proposed model gave best fusion result as compare to state-of-art methods. He used three different types of datasets. In past many exiting fusion methods also there but not produce discriminative representation for some datasets i.e. sparse, medium, dense residential aerial datasets and distinct objects such as tennis court, baseball fields and storage tanks. With this proposed method scene classification is improved and good tradeoff between classification accuracy & computational efficiency. This method leading to enhanced the feature discrimination **Bolei Zhou et.al. in [5]** has presented different-2 data sets of images for scene recognition. He defined the brief description of construction- steps of PLACES database. He has taken four different categories of datasets i.e. MIT indoor 67, ImageNet, SUN88, COCO and applied these datasets on three different architecture of CNN i.e. AlexNet, GoogLeNet, VGG16 and create benchmarks of given dataset. It trained all these architecture on Places datasets to create baseline CNN models. After the training processes this architecture become Place205-AlexNet, Place365-VGG etc. At the end compare the accuracy level of this CNN architecture on given datasets that contains 10 million images and showed how hybrid CNN architecture gave best accuracy i.e. 81.8% as compare to state-of-art methods. It allows machine algorithm to reach near-human semantic classifications of visual patterns. Solve the problem like spotting inconsistent objects and predicting future events. **BavinOndieki et.al.in [6]** used CNN for indoor and outdoor scene classifications. He used MIT Indoor 67 and SUN 397 datasets to match the requirements of industry standards. In addition by using Ethical-CNN-Fooling approach enhance or boost the performance parameters by 4%. In this paper CNN is trained on two different categories-first one is object-centric categories i.e. indoor scene detection, for e.g. table, chair, sofa and desktop, second category is scene-centric i.e. outdoor detection like mountains, roads, rivers etc. Furthermore feature enhancement technique also used to extract the feature from indoor scene categories. But indoor scene took more time as compare to outdoor scene detection. At last compare the difference properties of indoor & outdoor scene with the ethical CNN fooling approach. **Jia Deng et. al. in[7]** explained the construction of large scale database named as image net that consist 12 subtrees with 3.2 million of pictures. Author shows that it is larger in diversity & scale that gave better results in terms of accuracy for objects & image classification application. He defines the data collection with AMT. The aim of the author is to provide large amount of data online with high accuracy & diversity. It became central resource for vision related projects & research. **Jianxiong Xiao et. al. in[8]** author explained scene understanding(SUN) database with 397 categories of images. These categories contain 100 images in each set. In this paper author focused on relevant scene instead of study all scenes. He compared human scene classification with computer vision classification, how accurately man can identify out of hundred categories of images of men. He focused on particular/significant object in the scene rather than to study all scenes. For this he used different feature extraction techniques like GIST, HOG, SIFT, LBP, Sparse SIFT and Histograms. Out of 397 categories he took 15 different categories for defined features &kernals. Compare result with state of art method in terms of precision and recall. **Markus Koskelaet. al. in[9]** explained the four different categories of datasets using for scene classification.

Those dataset trained on convolutional neural networks and compared these categories on the basis of full image and spatial pyramids in terms of accuracy. Four categories are well defined that are Scenes-15, UIUC-Sports, Indoor-67 and SUN-397. Each category contained 200 to 400 images. With the use of CNN it provides universal representation for different picture recognition. Compared other network CNN is fast to extract even when applied on spatial pyramid structure images**. Hassan Ali Qaziet. al. in[10]** author explained the importance of action recognition. He took five different actions like clapping, boxing, waving, throwing & walking. He used feature detection techniques like HOG & SIFT and trained the esults on support vector machine. He gave the results in terms of accuracy & precision. ZHOU Li et. al. in[] described the structural & textural features in scenes classification instead of study the whole scene. He used SVM as a classifier and combining those feature on proposed detector that is WHGO (weighted histogram gradient orientation). Compare the results with existing SIFT descriptor and show that how WHGO gave better result in terms of structural feature extraction. **Ertugrual BAYRAKTAR et. al. in[11]** described different-2 performances of feature detector & descriptor methods. Some feature detectors are FAST, BRIEF, SURF, SIFT & BRISK. Five feature descriptors are SIFT, BRIEF, ORB, BRISK and SURF, Author used 23 different combinations of these detector and descriptors. It works on five different parameters i.e. time, accuracy, no. of correct matched key-points. Out of 23 combinations "FAST-SURF" combination provide good results in terms of angle & distance between correctly matched key-points.

"ORB-BRIEF" gave best result in terms of time consumption and SIFT-SURF gave best in terms of accuracy.

III. CONVOLUTIONAL NEURAL NETWORK FOR SCENE RECOGNITION

CNN consist mainly three layers: Convolutional, Pooling and Fully Connected. Convolution layers play the role of feature extractor. But they are not hand designed. Convolution filter kernel weights are decided on as part of the training process. Convolutional layers are able to extract the local features because they restrict the receptive fields of the hidden layers to be local [2]. Pooling Layer performs down-sampling. It diminishes the dimensionality of each component delineate holds the most imperative data. Spatial Pooling can be of various Kinds: Max, Average, Sum and so on. If there should arise an occurrence of Max Pooling, we characterize a spatial neighbourhood (for instance, a 2×2 window) and take the biggest component from the amended element outline that window. Rather than taking the biggest component we could likewise take the normal (Average Pooling) or total of all components in that window. Practically speaking, Max Pooling has been appeared to works better [2-5]. In CNNs, convolution layers play the role of feature extractor. However, they are not handplanned. Convolution channel piece weights are chosen as a major aspect of the preparation procedure. Convolutional layers can extricate the nearby highlights since they limit the responsive fields of the concealed layers to be neighbourhood. Theenhanced system structures of CNNs lead to saving in memory necessities and reducedcalculation complexity and, in the meantime, give better execution for applications where the info has nearby connection (e.g., picture and speech) [11-14].
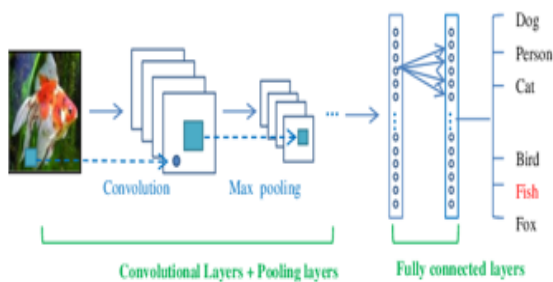
Fig. 1.CNN Basic Model

IV. MULTIPLE DATASETS

Computational work on place & scene recollection has systematized natural pictures within a bounded no. of semantic categories. However, any categories of dataset fail to click the accuracy & diversity of environments. Scene is the combination of objects & surroundings, like appearances of scenes are connected with particular behaviors & functions such as drinking in a café, praying in a temple, bathing in a bathroom, cooking in a kitchen, reading in a library , waiting in a waiting room and jogging in a garden. Scenes and their particular functions are nearly related to the visual navigation features that organize the space. In this paper we determine the five different scene categories with

different functionalities, instead of collecting whole scene we focused only on particular local and global features. After that we measured features on the behalf of accuracy from hundreds of categories of scenes [1,19].

Fig. 2.Dataset Categories (Indoor, Nature and Urban)

V. FEATURE DETECTORS METHODS

In terms of computer algorithms & visual application, we take picture as data in terms of numerical value. So raw image is not sufficient for perform any task and for this we used feature extraction techniques that consider the picture in the form of data and extract information from the data is called features. In scene recollection or computer visual system two types of feature detector are used to represent whole image i.e. global and local features. Global means "whole" feature vector where local means "particular selected regions of interest". For example in face picture if we consider whole features of face like nose, lips, eyes and cheeks that means global features worked on detection and if we are taking only particular feature like focused on only nose that time consider as global feature worked as recognition. Global describe the texture of feature, shape and contour representation. Local describes the texture of feature and detailed information of every key point. For scene classification and detection global feature detection techniques are used i.e. for low-level applications. For scene recognition local features detection techniques are used i.e. for high level application. HOG, shape matrices and CO-HOG are example of global descriptors where SIFT, LBP, MSER and FREAK are example of local detector [13]. The benefits of global descriptors are more compact and fast for easy to compute and take fewer amounts of memory but having occlusion and clutter limitations. So where we need invariant to useful transformation, local descriptor is used that takes sufficient amount of memory because focused on thousands point of an image. It is widely used in copy detection. Some properties are important of feature descriptors when it is using in scene recognition that are robustness, accuracy, generality & efficiency. It is divided into 3 categories-single, multiple and invariant detectors [18]. SIFT makes HOG orientations of given points in a portion about the key point and detect the highest value orientations within 80%. It used this value as the most powerful orientation of the key point. The algorithm of Sift starts by sampling the picture gradient orientations & magnitudes in 16*16 regions about every key point is using its scales to take the degree of Gaussian blur for a picture.

After those histograms orientation set is created where every histogram consists samples of 4*4 sub-regions of the real neighborhood and having 8 orientations in each bin. As the name indicate scale invariant feature transform and satisfied the properties like robustness, accuracy and illumination changes. It is useful for finding a particular part of an image[11-14].
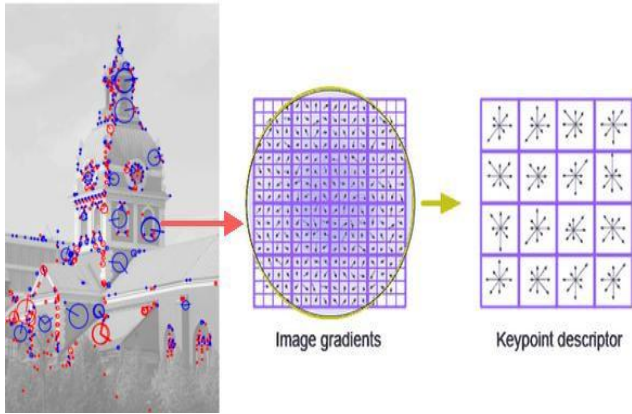

Fig. 3.SIFT descriptor

HOG is global descriptor widely used in detection of human body & body parts. It is used to calculate any size of image within fixed aspect ratio like 128*256, 64*128, 100*200 and 1000*2000 etc. HOG calculates the adjacent pixels of the gradient and widely used in pedestrian detection. It produced closer feature in different condition that makes classification easier. The main task of HOG is to describe whole feature vector instead of collection of features. It is used sliding window technique that moved around the picture. At every position of window detector, HOG computed its valve and shown to train support vector machine that classifies it either it is "image" or "not image" [6-9].
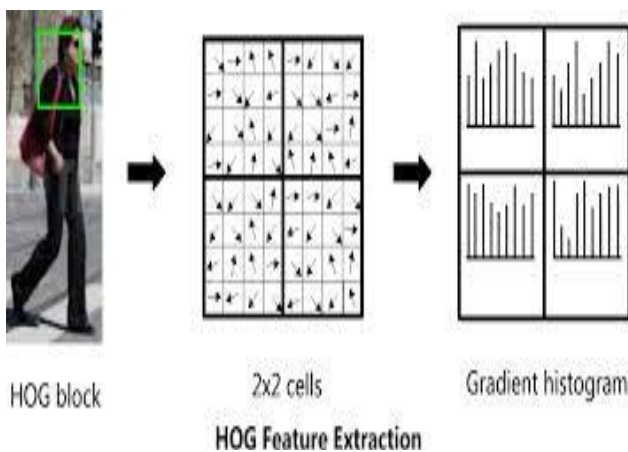

Fig. 4.HOG descriptor

After that direction & magnitude will be calculated. Further image is broken into cells and then HOG provides the estimation of each cells of an image. Important work of HOG in scene recognition to define the area of an image that is compressed internal representation makes scene more robust to noise. But it is still challenging task for real-time applications because huge amount of data to be processed in a second. Feature matching followed these steps [2, 4-8]:-
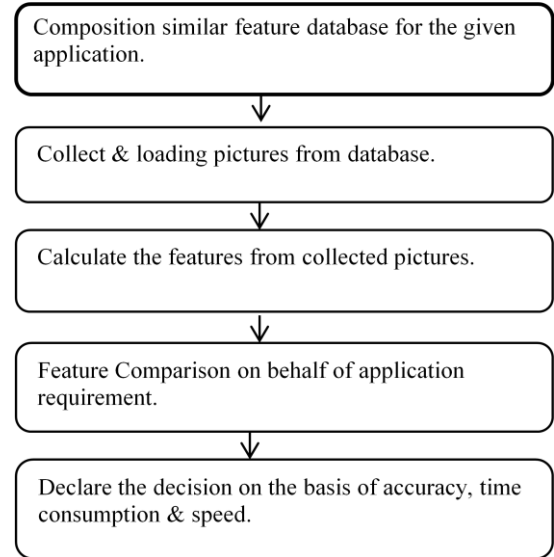

Fig. 5.Steps of feature matching

VI. PROPOSED ALGORITHM

Firstly to study the various image scenes recognition system development techniques. Then trained the Datasets on VGG- CNN Architecture for extract the features of the dataset using SIFT algorithm and to train the system using the extracted feature set, also to set the target of the extracted features for the HOG (Histogram Orientation Gradient). After extraction procedure evaluate the test image over the targeted dataset (CNN) and to evaluate the performance parameters like PNSR and MSE, ACCURACY. The last step of this algorithm is Comparison & Validation.
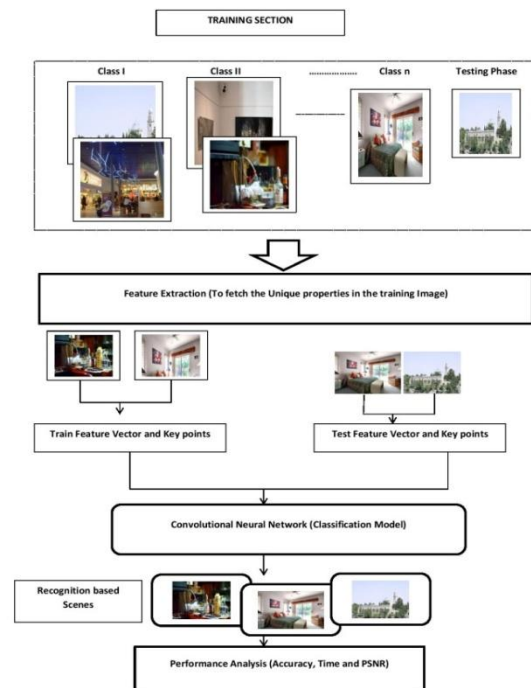

Fig. 6.Steps of Proposed Algorithm

Proposed Work Description:-Initialization, the scene recognition used for proposed work indoor and outdoor datasets. To create the knowledge based with various number of category are used. Upload the input image (RGB component) and convert the original image into Gray scale format to reduce the dimensions of the input image pixels. To check the interference in the given image of interference present then remove the distortion area in the image using filtration method and get the out image is smooth image. Smooth image calculation to detect the regions based on the different edges. Then we implement a SIFT algorithm to extract the features based on key points and parallel implement a HOG algorithm to fetch the extracted features based on components. In proposed algorithm has implemented a Hybrid approach (SIFT+HOG) method to extract the valuable feature in the form of key points and feature vector. It is unique feature calculation and after that CNN architecture implements to classify the feature set. In testing case, we analyse the train feature and test feature, if feature set values are same then predict or recognize the scene category image. If not then prediction failure occur and if successful then evaluate the parameters like Accuracy Rate, PSNR, Error rate. All performance metrics are compared to the existing algorithm.

VII.   RESULTS & DISCUSSION

Every classifier performance mainly depends upon the performance accuracy. High accuracy rate of a classifier shows better classification results and performance. Here as compare with the existing CNN architecture, HFCNN perform betters with high accuracy rate.

1.   Accuracy rate- For proposed architecture is more than 96% as calculated.
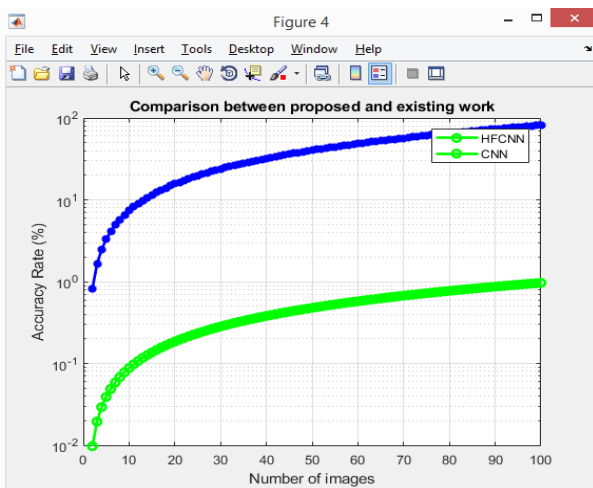

Fig. 7.Comparison - Accuracy Rate

$$AUC = \frac{\text{Correctly localized images}}{\text{Total images}} \times 100$$

Table 1: Comparison between proposed and existing work

Sample	Existing CNN	Proposed HFCNN
1	88.22	96.55
2	76.04	96.7
3	68.11	95.6
4	93.13	97.26

In the above table 1 the proposed architecture compared with some test cases and shows performance in terms of accuracy factor. Here as average accuracy as compare to the existing system shows high performance of proposed architecture with HFCNN.

2.   Time Consumption-Time consumption is a sum of total execution time to recognize the uploaded scene image sample. All execution and classification process is based on extracted feature and their simulation with training model. The total time to extract simulate feature vector with training model calculated. It shows the performance of Deep Learning model in terms of Time Factor. Small amount of execution time shows better performance of a deep learning model (HFCNN).
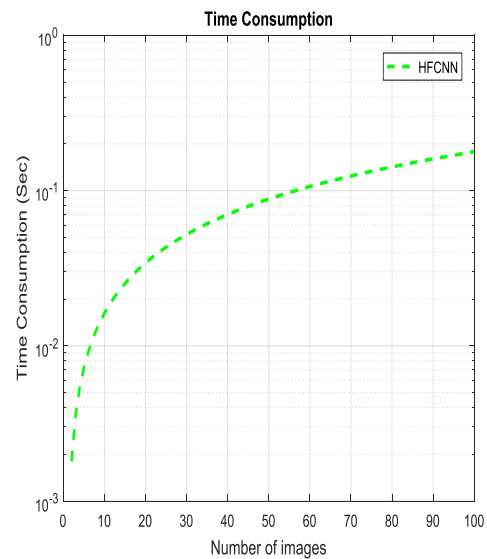

Fig. 8.Time Consumption (sec) in HFCNN

3.   PSNR of HFCNN-PSNR parameter is used to calculate the quality of image sample in the proposed architecture. It is basically filtered image quality achieved by the system for uploaded samples. High PSNR values show better results for the filtered sample in the proposed architecture.
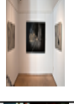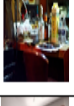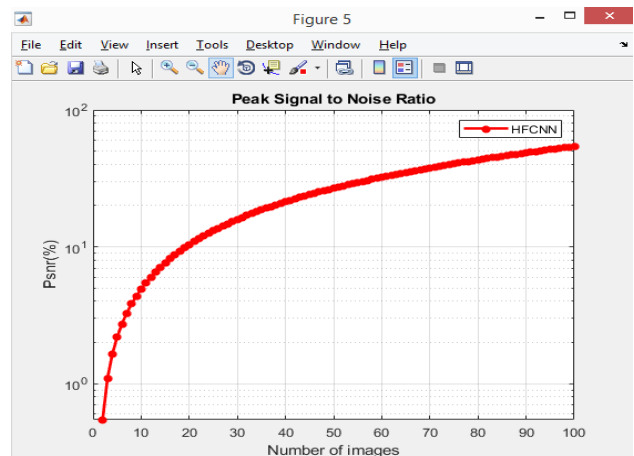

Fig. 9.PSNR of HFCNN

Table 2:- Performance Analysis with various Test cases (Class1)

Cat Name	Test Image	Accuracy Rate	FAR	FRR	MSE	PSNR	Time Consumption
Abbey		0.9690	0.0098	0.0099	0.0212	54.016	0.17
Airports		0.970	0.0099	0.0092	0.0202	53.499	0.166
Art Gallery		0.965	0.0003	0.00034	0.00343	56.23	0.15
Bar		0.9642	0.00035	0.0035	0.035	58.2	0.20
Bedroom		0.9723	0.0096	0.0097	0.0234	52.2	0.18

VIII. CONCLUSION

In the existing scene recognition model, the generic features have been utilized to determine the type of image scenes. The multi-feature amalgamation is not performed, which covers the merging of colour and texture based features together to observe the join features of the data. This absence of feature amalgamation is the key point behind the lower accuracy. In this paper we used significant feature approach for scene classification instead of classify whole scene because in many applications focused on particular things. It improves accuracy with lower time consumption. Our proposed method HFCNN gave better accuracy i.e. approx. 96% that is much higher than exiting method that gave 81% and time consumption rate is 0.15-0.20 sec.

FUTURE SCOPE

Our proposed method gave results in terms of accuracy, time consumption, PSNR and cost effective because it took simple CNN architecture for scene classification i.e. VGG-CNN architecture. It used HOG+ SIFT combination for feature extraction instead of the use of SURF+ FREAK or FAST+BRISK that is higher in terms of cost as compare to SIFT and HOG. So it is suitable all the computer and robotics application where cost and time is matter with accuracy for multiple datasets.

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