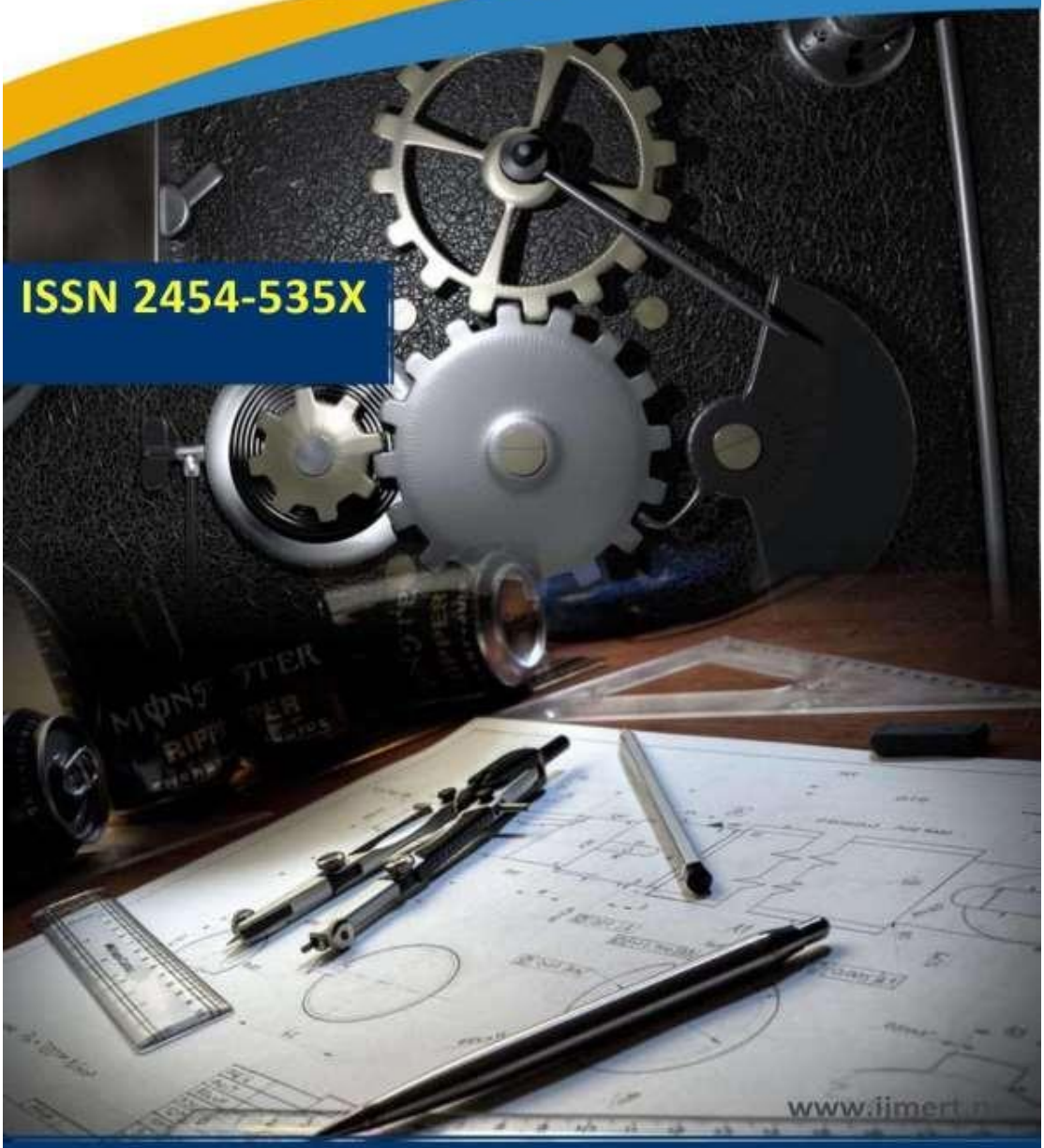
International Journal of Mechanical Engineering Research and Technology

ISSN 2454-535X



Email ID: info.ijmert@gmail.com or editor@ijmert.net

International Journal of Mechanical Engineering Research and Technology
ISSN 2454 – 535X www.ijmert.com
Vol. 15 Issue. 4, Dec 2023

CONTENT BASED IMAGE RETRIEVAL USING DEEP LEARNING

J. VENKATESH[1], PATLOLLA UMA MAHESHWARI[2], MARUTURI MANOJ KUMAR[3], MANNE SAHITHI[4], POKALKAR JEEVAN[5]

[1] Assistant Professor, Dept of CSE, MALLA REDDY INSTITUTE OF ENGINEERING AND TECHNOLOGY(AUTONOMOUS),Dhulapally,Secundrabad, Hyderabad, Telangana, India.

[2,3,4,5] UG Students, Dept of CSE, MALLA REDDY INSTITUTE OF ENGINEERING AND TECHNOLOGY(AUTONOMOUS),Dhulapally,Secundrabad, Hyderabad, Telangana, India.

ABSTRACT:

Content-Based Image retrieval(CBIR) is a technique to search and retrieve similar images from large multimedia databases and an IR system is regarded as efficient if it can retrieve all the images to meet the user's needs. There are many advancedmachine-learning technologies such as deep neural networks(DNN), convolutional neural networks(CNN), and transfer-learning(TL), which are gaining greater importance in image-related tasks. In this paper an efficient framework for content-based image retrieval system adapting transfer-learning on pre-trained CNNs (ResNet18, GoogLeNet, AlexNet) using query-by-image method is proposed, the method explores classification-score descriptors for IR and employ distance metrics for similarity matching. The framework prescribes transfer-learning for efficient retraining of pre-trained CNNs on small datasets chosen from the Wang database. Thirty-plus experiments are designed for finding optimal values of the hyper-parameters and exploring the suitability of six popular distance metrics namely Euclidean, seuclidean, Cityblock, Cosine, Mahalanobis, and Chebychev. After extensive experimentation, a new efficient framework for CBIR using CNN classification scores is proposed and the new framework of CBIR achieves the image retrieval accuracy of 99.45% on natural scene images of 20 classes of the Wang dataset. The experimentation show that the proposed framework is efficient for content-based image retrieval system

Keywords: CNN, CBIR, TL, ANN.

International Journal of Mechanical Engineering Research and Technology
ISSN 2454 – 535X www.ijmert.com
Vol. 15 Issue. 4, Dec 2023

1. INTRODUCTION:

The advancement in information technology has resulted in an ever-increasing quantity of multimedia data. Automated systems for analyzing, classifying, indexing, and retrieval of multimedia data are necessary, and the available computer-assisted automatic systems are facing the challenge of a "semantic gap" in the retrieval of multimedia information. The works in image retrieval date back to the 1980s with image annotation and keyword-based querying [1] on image database management (IDBM) systems. The keyword-based search is dependent on the quality and completeness of image annotations. In order to increase the efficiency of image retrieval and to reduce the work of annotation and its related discrepancies,content-based image retrieval (CBIR) systems are introduced. But these required the process of feature extraction to understand the contents of the image queries. Such visual interactions via the query-by-visual example and query-by-subjective descriptions for CBIR are explained in [2] and CBIR systems (IBM's QBIC to Chabot) are summarized in [3], [4] to increase the search efficiency and retrieval accuracy. But the use of visual features such as color, texture, shapes (the low-level features), etc. to retrieve relevant images, results in lack of understanding the human perceptions such as objects, events, etc. Since the performance of CBIR systems heavily depends upon the feature descriptors, matching the low-level visual contents of images to high-level understanding (Bridging the semantic gap) becomes essential to meet the user needs. The semantic gap can be reduced by creating the object ontology, using supervised and unsupervised machine learning methods, relevance feedback, generating semantic templates, using web info [5], etc., and are summarized.

Assistant Professor, Dept of CSE, MALLA REDDY INSTITUTE OF ENGINEERING AND TECHNOLOGY(AUTONOMOUS), Dhulapally, Secundrabad, Hyderabad, Telangana, India.

2. LITERATURE SURVEY

Image retrieval techniques are extremely useful in content management systems, according to Gopal and Bhooshan (2015). For

International Journal of Mechanical Engineering Research and Technology
ISSN 2454 – 535X www.ijmert.com
Vol. 15 Issue. 4, Dec 2023

retrieving identical images from databases, CBIR strategies integrate explicit image features such as hues, surfaces, key points, and so on. Grayscale information is used in a large number of key point detectors and key point descriptors. By adding additional shading information to the key point descriptors, the retrieval accuracy of these strategies can be enhanced. An enhanced SURF descriptor for CBIR applications is proposed in this paper, which extracts image features by processing Hu minutes along with eigen values in the immediate vicinity of the specified key points. The use of an improved SURF descriptor improves image retrieval performance in the lab. Furthermore, the improved SURF descriptor can distinguish between images of the same object with identical grayscale properties but different hues. J. Wan, D. Wang, and S.C.H. Hoi, 2014. Learning good feature representations and similarity measures is critical to a CBIR framework's retrieval efficiency. Despite decades of study, it remains one of the most difficult open issues that significantly impedes the progress of real-world CBIR frameworks. The main problem has been due to a significant semantic difference between low-level image pixels captured by machines and high-level semantic ideas seen by humans. Machine learning has been actively explored as a possible path to bridge the semantic gap in the long run, among other approaches. We investigate the state-of-the-art deep learning procedures for learning feature representations and similarity measures, sparked by recent successes of deep learning strategies for PC vision and other applications, to answer an open issue: whether deep learning is an expectation for connecting the semantic gap in CBIR and how much upgrades in CBIR tasks can be accomplished by investigating the state-of-the-art deep learning procedures for learning feature representations and similarity measures. Especially, By analyzing a stateof-the-art deep learning technique CNN for CBIR tasks under various set-chimes, we examine a theory of deep learning with application to CBIR tasks with a wide array of empirical examinations. P. Nalini and B.L. Malleswari, 2016 CBIR is a technique that recovers similar images based on image content similarity for a given query image. The visual features of an image, which are mathematical representations of a digital image, are referred to as image material. The image retrieval task is primarily based on

International Journal of Mechanical Engineering Research and Technology
ISSN 2454 – 535X www.ijmert.com
Vol. 15 Issue. 4, Dec 2023

image feature extraction and feature vector similarity calculation. The output of the CBIR process is determined not only by the ideal features extracted from the picture, but also by the best possible decision of the CBIR process. Tests of similarity and dissimilarity (distance metrics). Since the image features vary so greatly in terms of colouring, surface, and form, using the same distance metric for all of them does not work well. We first provided an overview of the mathematical and statistical distance metrics used in CBIR, as well as a comparison of these measures on shading and surface features in this paper. Surface features are extracted by wavelet deteriorations and shading features are extracted by figuring shading histograms in HSV room.For feature similarity, geometrical distances such as Manhattan, Chebyshev, and Euclidean were analysed, as well as statistical distance metrics such as Cosine Similarity, Chi-square, KullbackLeibler, Jeffrey, and cumulative statistical distance metrics such as KolmogorovSmirnov, Cramer von Mises, and Earthmovers distances. With shading and surface features separately, we set specific goals for the performance of all of these distance metrics in terms of Mean Average Precision (MAP) and Recall rates.

PROPOSED SYSTEM:

The combination of convolution neural networks (CNN) and deep learning generated a stunning result in a variety of image processing applications. For separating comparable images, CNN-based techniques to isolate image features from the last layer and the use of a single CNN structure could be used. The ContentBased Image Retrieval system is used to learn highlight extraction and efficient similarity examination (CBIR). Highlight extraction, like similarity tests, plays an important role in CBIR. The research is carried out using datasets such as the UC Merced Land Use Dataset. Using a pre-trained model that has been adjusted for the retrieval task and has been trained on a large number of photographs. For the retrieval process, pre-trained CNN models are used to generate image highlight descriptors. By using move learning and retrieval of highlight vectors using various similarity measures, this technique manages component extraction from the two completely connected layers present in the VGG-16 network.

International Journal of Mechanical Engineering Research and Technology
ISSN 2454 – 535X www.ijmert.com
Vol. 15 Issue. 4, Dec 2023

3. METHODOLOGY

The proposed strategy includes extracting image feature vectors from the pre-trained CNN model's two completely linked layers. Since the datasets contain fewer files, the pre-trained CNN loads of the ImageNet model can be used for retrieval. It is possible to use the loads legitimately and architecture learning and apply the learning to the CBIR tasks by using pre-trained models that have been trained on a large number of image datasets. This is transfer learning, which involves passing knowledge to a pre-trained model based on the problem statement that has been assigned.

The information image provided as a query can come from any source, and it is not required to come from the datasets. The query image is taken from the datasets in this case. The features are derived from the AlexNet layers, and the yield classification layer is the final layer. Since transfer learning allows the pretrained model to be adjusted. It is the process of removing the final yield classification layer from the architecture and using the remaining architecture as a fixed feature extractor. These extracted features were used to compare the query input image to image database features using a variety of similarity metrics. A limit value is set for sifting through the images that are identical to the information image and those that are not similar based on the value of similarity measures taken. As a result, the value of similarity above the edge will be sifted through, and the proposed approach will deal with image similarity assessment using different distance metrics.

CONCLUSION

The efficiency and accuracy of the image retrieval system will be improved by initializing the pre-trained model trained on ImageNet for new images. It is possible to recover new images with superior output using these pre-trained models as well as transfer learning. Similar images are retrieved by registering the similarity of features from both fully connected layers. The retrieval from the Fc2 layer is more efficient than the Fc1 layer retrieval. For all distance steps, the retrieval performed from the Fc2 layer has a higher precision rate. The Euclidean distance and Cosine similarity are used in both datasets to find the most related images. When recovering images from the Fc2 layer in the UC Merced Land Use dataset, the rate of precision for Euclidean Distance and Cosine Similarity, respectively, is 0.92 and 0.96.

International Journal of Mechanical Engineering Research and Technology
ISSN 2454 – 535X www.ijmert.com
Vol. 15 Issue. 4, Dec 2023

In the SceneSat dataset from the Fc2 sheet, both Euclidean Distance and Cosine Similarity are 0.96.

REFERANCES

[1] Singh, A.V. Content-based image retrieval using deep learning. Rochester Institute of Technology, 2015.

[2] Krizhevsky, A., Sutskever, I. and Hinton, G.E. Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems, 2012, 1097-1105.

[3] Yasmin, M., Mohsin, S. and Sharif, M. Intelligent image retrieval techniques: a survey. Journal of applied research and technology 12 (1) (2014) 87- 103.

[4] Bagyammal, T., and Parameswaran, L. Context Based Image Retrieval using Image Features. International Journal of Advanced Information Science and Technology 29 (2014). Bakar, S.A., Hitam, M.S. and Yussof, W.N.J.H.W. Content-Based Image Retrieval using SIFT for binary and greyscale images. IEEE International Conference on Signal and Image Processing Applications (ICSIPA), 2013, 83-88.

[5] Gopal, N. and Bhooshan, R.S. Content Based Image Retrieval using enhanced SURF. Fifth National Conference on, Computer Vision, Pattern Recognition, Image Processing and Graphics, 2015, 1-4.

[6] Wan, J., Wang, D., Hoi, S.C.H., Wu, P., Zhu, J., Zhang, Y. and Li, J. Deep learning for contentbased image retrieval: A comprehensive study. Proceedings of the 22nd ACM international conference on Multimedia, 2014, 157-166.

[7] Babenko, A., Slesarev, A., Chigorin, A. and Lempitsky, V. Neural codes for image retrieval. European conference on computer vision, 2014, 584-599.

[9] Nalini, P. and Malleswari, B.L. An Empirical Study and Comparative Analysis of Content Based Image Retrieval (CBIR) Techniques with Various Similarity Measures. 3rd International Conference on Electrical, Electronics, Engineering Trends, Communication, Optimization and Sciences, 2016, 373-379.