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Design An Advanced Model for Image Classification Based on Neural Network Architecture: An Implementation

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KEYWORDS

Object detection, Deep CNN, Features fusion, Features reduction, Classification.

ABSTRACT:

In the field of machine learning and pattern recognition, object classification has garnered significant interest due to its wide-ranging applications, including visual surveillance. Despite the emergence of numerous deep learning-based methods for object classification, persistent challenges continue to affect overall classification accuracy. Complex backgrounds, crowded scenarios, and object similarity remain among the key obstacles. To address these challenges, we propose a technique that combines deep convolutional neural networks (DCNNs) with scale-invariant feature transform (SIFT). Initially, an enhanced saliency method is employed to identify relevant points, from which features are extracted.

1 THEORETICAL BACKGROUND

The highest objective of our examination is to investigate whether profound learning can address the semantic hole in CBIR better than customary elements. Utilizing profound CNN models, we can support the recovery execution by utilizing the gained include portrayals from them. Here we plan to gadget a structure to extricate highlights from different profound CNN models and apply them for picture recovery activity with comprehensive investigations under fluctuated settings.

All the more especially, we expect to track down deals with serious consequences regarding beneath recorded significant inquiries:

1) Whether profound convolutional brain organizations (CNN) models are the most ideal for learning powerful component descriptors that can be utilized in picture look and recovery activity?
2) Whether recovery execution can be improved by utilizing profound CNNs in contrast with existing CBIR techniques?
3) Whether profound CNN model prepared in a specific space can deliver better picture recovery brings about different spaces?
4) Is it conceivable to utilize more than one pre-prepared profound CNN model all the while in picture recovery activity?
5) How might we at any point make a profound CNN model more significant by learning on our datasets and simultaneously outwit the pre-prepared model with no guarantees?

2 CONVOLUTIONAL NEURAL NETWORKS

Brain organizations can be carried out as a particular example, similar to a convolutional brain organization. The CNN execution imitates a human cerebrum's visual cortex working. The visual cortex is answerable for visual component in people. As framed in Fig 2.1, each layer abstracts inputs from a gathering of highlights from the previous layer's little locale. Such districts are named as neighborhood responsive fields. These fields help to infer unique significant elements that can portray a picture outwardly.

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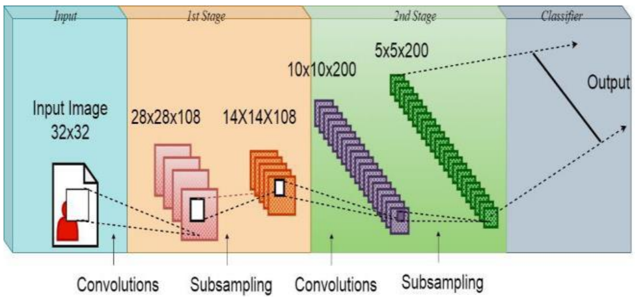

Fig. 2.1 Block diagram of a run of the mill CNN

The CNNs are applied in diverse applications, the important ones are pattern and object recognition, language and speech recognition, and video analysis, etc.

3 PASCAL3D + V1.1 DATASET RESULTS

In this section, we present the proposed computation results on PASCAL 3D dataset. The still up in the air in four exceptional advances: a) AlexNet significant CNN features extraction close by entropy-controlled incorporate assurance, b) VGG features extraction and entropy controlled assurance, c) mix of VGG and AlexNet significant CNN features close by assurance procedure, and d) mix of Channel and significant CNN features close by entropy controlled technique. Three limits (i.e., precision, FNR, and time) are used to measure the presentation of each and every classifier. As discussed over, this dataset includes outright 22,394 pictures of 12 unique thing classes. For endorsement of the proposed strategy on this dataset, we pick a philosophy of 50:50 for getting ready and testing. This approach is followed for each step. The refined best portrayal precision for AlexNet significant CNN features close by entropy-controlled assurance procedure is 76.8% on social affair classifier. The FN rate on

Table 3.1 Examination with existing strategies

Paper	Year	Features	Technique	Accuracy (%)	Time (s)
Jun et al. [38]	2018	2000 after PCA on 4096	Deep Stack Network	89	
Jinjoo et al. [57]	2018	SIFT->SVM	SSPCA	83.9	
Qing et al. [38]	2018	YCbCr-SIFT	YCbCr-SIFT+LSC+ELM	78	
Yongsheng et al. [45]	2018	SIFT	Reduction using K Means	85.78	
Xiaozhao et al. [13]	2018	Salient features using unsupervised	PCA->1500	76	
Ridha et al. [9]	2017	Deep CNN	Fast wavelet	75.6	
Our	2018	Deep CNN and SIFT Features	Fusion of Deep CNN and SIFT Features along with entropy-controlled selection method	**20 Classes: 86.5** **34 Classes: 93.8** **50 Classes: 93.5** **100 Classes: 89.7**	**75.70** 289.90 **178.20** **302.50**

The acknowledgment consequences of a gathering classifier are likewise contrasted and other cutting edge grouping techniques as introduced in Table 6. In the subsequent step, the arrangement is performed by utilizing VGG-19 profound CNN includes and accomplished most extreme characterization precision 81.8%, which is worked on when contrasted with AlexNet highlights. However, the execution time on VGG-19 profound highlights alongside the choice technique is expanded on troupe classifier and best accomplished execution time is 240.86 s on choice tree as given in Table 5.6. In the third step, chose AlexNet DCNN and VGG DCNN highlights are melded by a sequential based strategy and perform characterization. The best-accomplished characterization exactness is 87.4% on troupe classifier, which is fundamentally worked on after combination of DCNN highlights. The execution season of gathering classifier for stage 3 is 230.2 s, which is higher than the FKNN as introduced in Table.

3.1 Segmentation Using Improved Saliency Method

3.1.1 SIFT Features

The Filter highlights are processed in four stages. In the initial step, neighborhood central issues are resolved that are significant and stable for given pictures. The elements are separated from each central issue that makes sense of the neighborhood picture district tests, which are

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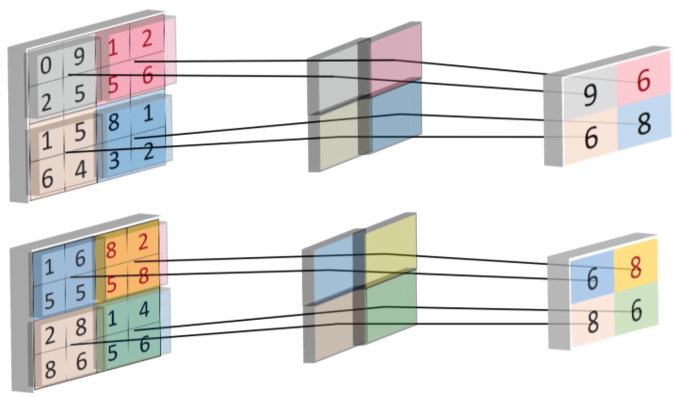
connected with its scale space coordinate picture. Then in the subsequent step, powerless highlights are eliminated by a particular edge esteem. In the third step, directions are doled out to each central issue in view of nearby picture angle bearings. At long last, 1x128 layered include vector is gotten and perform bilinear introduction to work on the strength of elements.

3.1.2 Deep CNN Features

In this article, we used two pre-arranged significant CNN models, for instance, VGG19 and AlexNet, which are used for features extraction. These models combine convolution layer, pooling layer, normalization layer, ReLu layer, and FC layer. As discussed over that convolution layer eliminate close by features from an image.

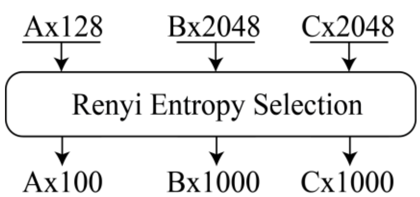
3.1.3 Features Extraction

Max Pooling



3.1.4 Feature Selection

We utilized entropy based highlight Determination in this way to deal with lessen the separated element.



3.1.5 Feature Fusion

We utilized Sequential based Element combination

$$(\boldsymbol{Fused}) = (N \times 1000) + (N \times 1000) + (N \times 100)$$

$$(\boldsymbol{Fused}) = N \times fi$$

The size of conclusive component vector is 1 × 2100, which feed to gathering classifier for arrangement. The gathering classifier is a directed learning technique, which need to preparing information for expectation.

Outfit technique consolidates a few classifiers information to create a superior framework.

3.1.6 Results

Proposed Method:

1. Improved Saliency Method:

- Use an improved saliency approach (based on HDCT) to distinguish and section the salient object from the input image.
- Apply LAB color space transformation before saliency detection for better results.

2. Feature Extraction:

- Extricate Filter (Scale-Invariant Component Change) point highlights from the segmented RGB object image.
- Use pre-trained DCNN models like VGG-19 and AlexNet to remove profound CNN highlights by applying initiation on the completely associated (FC) layer.

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3. Feature Selection:

- Employ a Renyi entropy-controlled method on the SIFT and DCNN feature matrices to select the most robust features.
- Sort the highlights in view of entropy values and select the top K features (e.g., 1000 from AlexNet, 1000 from VGG-19, 100 from SIFT).

4. Feature Fusion:

- Fuse the selected DCNN features (AlexNet and VGG-19) and SIFT features into a single matrix using a serial fusion approach.

5. Classification:

- Feed the fused feature matrix to an ensemble classifier (e.g., Ensemble Boosted Trees) for object classification.

3.2 Experiments and Results:

- Evaluated on three datasets: Caltech-101, Pascal 3D+, and a 3D dataset.
- Achieved classification accuracies of 93.8% (Caltech-101), 88.6% (Pascal 3D+), and 99.7% (3D dataset).
- The proposed fusion of DCNN furthermore, Filter highlights with entropy-controlled determination outperformed individual features and existing methods.
- Reduced execution time compared to using only DCNN or SIFT features.

In summary, the proposed method combines improved saliency object segmentation, deep CNN feature extraction from pre-trained models (VGG-19 and AlexNet), SIFT point features, entropy-based robust feature selection, and feature fusion for efficient image classification using an ensemble classifier. The fusion of complementary features and intelligent selection approach led to high accuracies across multiple datasets.

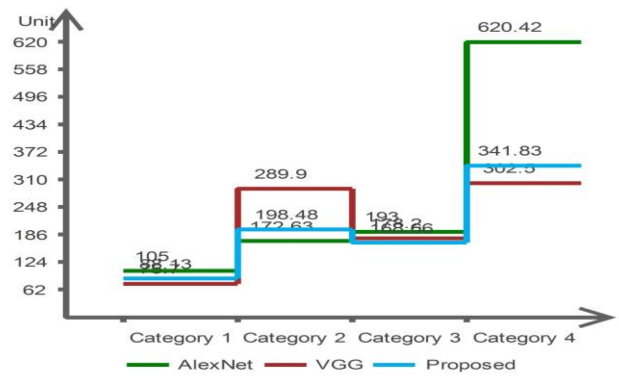

Fig. 3.1 Correlation of the execution season of all characterized probes the Caltech101 dataset

Table 3.2 Grouping exactness on PASCAL 3D dataset

Method	No of classes				Performance measures		
	AlexNet-Entropy	VGG-19-Entropy	Fused DCNN-Entropy	Fused SIFT+DCNN+Entropy	Accuracy (%)	FNR (%)	Time (seconds)
Ensemble boosted tree	✓				**76.8**	**23.2**	**154.5**
		✓			**81.8**	**18.2**	304.8
			✓		87.4	**12.6**	230.2
				✓	**88.6**	**11.4**	**111.99**
Linear SVM	✓				71.0	29.0	437.18
		✓			78.1	21.9	626.3
			✓		56.6	43.4	834.9
				✓	82.8	17.2	175.26
QSVM	✓				75.6	24.4	641.2
		✓			80.6	19.4	698.2
			✓		86.9	13.1	1821.7
				✓	81.3	18.7	210.39
CSVM	✓				73.6	26.4	600.57
		✓			79.1	20.9	765.77
			✓		86.6	13.4	1211.2
				✓	81.4	18.6	217.5
FKNN	✓				64.0	36.0	195.068
		✓			70.8	29.2	222.43
			✓		75.0	25.0	**198.71**
				✓	23.4	76.6	134.934
CKNN	✓				71.5	28.5	2149.1
		✓			78.9	21.1	5277.1
			✓		82.6	17.4	4133.5
				✓	26.5	83.5	659.35
Decision tree	✓				70.6	29.4	164.36
		✓			78.0	22.0	240.86
			✓		82.6	17.4	398.78
				✓	73.85	26.15	185.585
WKNN	✓				64.7	35.3	1087.5
		✓			71	29	2457.3
			✓		74.8	25.2	2020.2
				✓	78.2	21.8	409.78

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The intense qualities shows the best outcomes

Finally, the proposed strategy results on PASCAL 3D dataset are differentiated and existing systems as presented in Table 3.2.

3.3 Result and Discussion

The paper by Rashid et al. proposes another method for object recognition and arrangement that joins profound convolutional brain organizations (DCNNs) and scale-invariant component change (Filter) point highlights. The inspiration is to further develop object grouping exactness, particularly in testing situations with complex foundations, jumbled scenes, and outwardly comparable article classes.

The proposed technique comprises of two fundamental equal advances. The initial step includes applying a better saliency-based strategy to remove Filter point highlights from fragmented object areas in RGB pictures. The subsequent step separates profound CNN highlights from pre-prepared models like VGG-19 and AlexNet by performing enactment on the completely associated layer.

To choose the most vigorous and discriminative highlights, an entropy-controlled include decrease technique in view of Renyi entropy is applied to both the Filter point elements and profound CNN highlights. The chose highlights from the two sources are then melded utilizing a sequential methodology into a consolidated element vector.

At long last, this combined element vector is given as contribution to a troupe classifier for object acknowledgment and order. The proposed technique is assessed on three freely accessible datasets: Caltech-101, Pascal 3D+, and a 3D item dataset.

3.3.1 Improved Saliency Method for Object Segmentation

The first step employs an improved saliency technique to detect and segment the primary object from each input image. This builds upon an existing saliency estimation method called HDCT (high-dimensional color transform).

The key enhancement is to first apply color space transformation from RGB to L*a*b* color space before providing the image to the saliency algorithm. The L*a*b* color space separates the lightness dimension (L*) from the color dimensions (a* and b*), which can help better identify salient object regions.

The saliency map is computed based on both color statistics in L*a*b* space as well as spatial information using superpixel segmentation. A Trimap is constructed using adaptive thresholding to identify the highly salient pixels corresponding to the foreground object.

This improved saliency method allows better segmentation of the primary object from the background, providing a good initialization for subsequent feature extraction focused on the object of interest. Sample results show effective segmentation of objects like cars, chairs, faces etc. from input images with complex backgrounds.

3.3.2 Scale-Invariant Feature Transform (SIFT)

After object segmentation, SIFT point features are extracted from the segmented RGB object regions mapped back from the saliency results. SIFT is a well-known hand-crafted feature extraction technique that identifies stable keypoints in images and computes a 128-dimensional feature vector describing the local image patch around each keypoint.

The SIFT feature vectors are designed to be invariant to image scaling, rotation, illumination changes and other transformations. This robustness makes SIFT an excellent complementary representation to learn along with the deep CNN features.

The SIFT features are extracted according to the standard procedure of:

1) Detecting potential interest keypoints
2) Localizing the keypoints with high stability
3) Assigning orientations based on local gradients
4) Computing the 128-dimensional SIFT descriptor vector for each keypoint

SIFT key points and descriptors provide a sparse, robust representation of the segmented object that can distinguish it from background clutter and capture fine-grained details missed by deep CNN features.

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3.3.3 Deep CNN Feature Extraction

For profound CNN highlight extraction, the creators use two well known pre-prepared models - VGG-19 and AlexNet. These models have been trained on the large ImageNet dataset and can transfer their learned representations to new object classification tasks.

The VGG-19 network contains 16 convolutional layers and 3 completely associated layers, while AlexNet has 5 convolutional layers and 3 completely associated layers. Both networks employ convolutional filters to extract local features which are combined through pooling layers to generate higher-level representations in the fully-connected layers.

To extricate profound highlights, the info RGB picture is gone through the convolutional and pooling layers of the pre-prepared VGG-19 and AlexNet models. Then, at that point, initiation is applied on the second completely associated layer (fc7) to obtain the 4096-dimensional activation vector capturing high-level semantic information about the objects present.

Since the 4096-D fc7 feature vector is high-dimensional and may contain redundant information, max-pooling with a 2x2 filter is applied to reduce it to a 2048-D feature vector while retaining the most discriminative features.

The deep CNN features from VGG-19 and AlexNet provide a compact, high-level representation of the object shape, texture, and semantic category, complementing the low-level local details captured by SIFT. However, the deep features alone may not be sufficient for fine-grained discrimination between visually similar objects or objects in cluttered environments.

3.3.4 Entropy-Controlled Feature Selection

To select the most robust and non-redundant deep CNN and SIFT features for subsequent classification, the authors propose an entropy-controlled feature reduction method based on Renyi entropy.

Renyi entropy is a summed up type of Shannon entropy that characterizes the information richness and randomness present in a signal or feature space. It can estimate the intrinsic dimension or complexity of the feature space.

The Renyi entropy H(X) of a probability distribution P = {p1, p2, ..., pn} is defined as:

$$H(X) = (1/1-\alpha) * \log(\mathrm{Sum}(pi\hat{}\alpha)) \quad \text{for } \alpha >= 0, \alpha != 1$$

Where α is the order of the entropy measure. As α approaches 1, Renyi entropy converges to Shannon entropy.

In the proposed method, Renyi entropy is computed separately on the 2048-D max-pooled feature vectors from VGG-19 and AlexNet, as well as the 128-D SIFT feature vector. The entropy values quantify the information richness of each feature subspace.

3.3.5 Feature Fusion

After selection, the deep CNN features from VGG-19 (1000-D) and AlexNet (1000-D) are combined through serial fusion into a 2000-D vector representing high-level semantic information. This fused deep CNN feature vector is further concatenated with the 100-D SIFT vector using serial fusion.

The final fused feature vector has a dimensionality of 2100, dense enough to capture multi-scale cues about the object's shape, texture, semantic category and local details. By combining complementary information from pre-trained deep models and hand-crafted descriptors, the fused features are expected to be more discriminative for classification compared to either source alone.

However, fusing heterogeneous features into a high-dimensional vector also increases the risk of including noisy or redundant features that could degrade classification accuracy. This motivates the need for the entropy-controlled selection scheme prior to fusion.

3.3.6 Classification Using Ensemble Boosted Trees

For object classification, the 2100-D fused feature vector is provided as input to an ensemble boosted tree classifier from the Matlab Statistics and Machine Learning Toolbox.

Ensemble methods train multiple base learners (e.g. decision trees) on randomly perturbed subsets of the

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training data, then combine their outputs through techniques like bootstrap aggregation (bagging) or boosting to reduce variance and bias compared to single classifiers.

Boosted tree ensembles iteratively train a sequence of weak decision tree learners focused on examples misclassified by previous trees, with a weighted majority vote determining the final ensemble prediction. They can effectively model non-linear decision boundaries while being relatively robust to noisy features and outliers.

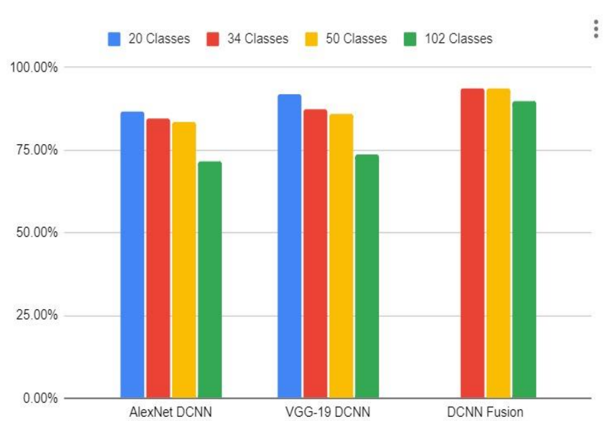
3.3.7 Experiments on Caltech-101 Dataset

The Caltech-101 dataset comprises of 9,144 pictures across 102 article classifications, with 31 to 800 pictures for each class. It contains a variety of objects like faces, vehicles, animals, household items etc. in different orientations and environmental settings with variable backgrounds.

The creators direct trials on Caltech-101 utilizing 3 unique strategies:

1) AlexNet DCNN features with entropy assurance
2) VGG-19 DCNN features with entropy assurance
3) Fusion of DCNN (VGG-19 + AlexNet) and Channel features with entropy decision

For each procedure, they erratically test subsets of 20, 34, 50 and every one of the 102 classes and evaluate the request precision of different strategies using 10-cross-over cross-endorsement with a 50:50 train-test split.



3.4 AlexNet DCNN WITH ENTROPY SELECTION

Using just AlexNet DCNN features reduced by Renyi entropy, the ensemble classifier achieves a maximum accuracy of:

- 86.5% for 20 classes
- 84.6% for 34 classes
- 83.5% for 50 classes
- 71.7% for all 102 classes

The high dimensionality and visual similarity between many classes in Caltech-101 makes it a challenging dataset even for deep features. Performance degrades as more classes are added, but the entropy selection scheme ensures the ensemble outperforms SVMs and KNNs.

3.4.1 VGG-19 DCNN with Entropy Selection

Switching to the deeper VGG-19 architecture along with entropy selection boosts the maximum ensemble accuracy to:

- 92.0% for 20 classes
- 87.5% for 34 classes
- 86.0% for 50 classes
- 73.8% for 102 classes

VGG-19 extracts richer semantic features that improve accuracy over AlexNet across all class subsets. However, the 102-class result of 73.8% suggests discriminating between so many fine-grained categories remains very challenging for deep features alone.

3.4.2 Fusion of DCNN and SIFT with Entropy Selection

The proposed fusion approach that combines deep CNN features from VGG-19 and AlexNet with SIFT point features, followed by entropy-controlled selection, achieves the best performance:

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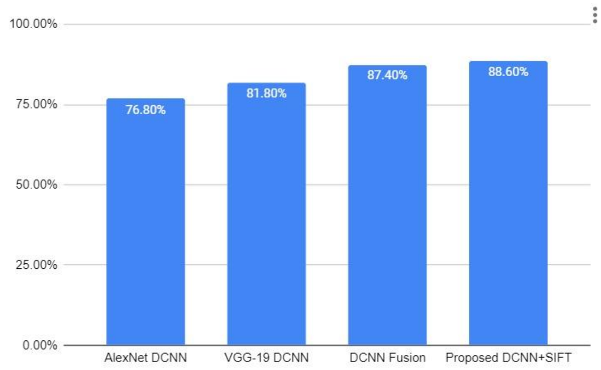

- 93.8% accuracy for 34 classes
- 93.5% accuracy for 50 classes
- 89.7% accuracy for 102 classes

This substantiates the complementary nature of deep semantic features and traditional hand-crafted local descriptors like SIFT. The entropy selection scheme effectively identifies the most discriminative features from each source to fuse into a powerful combined representation.

4 CONCLUSION

The proposed procedure works in two equivalent advances. The greatest pooling is performed on removed features organizations to dispose of the boisterous information. From that point on, a Reyni entropy-controlled methodology is proposed which control the inconsistency of isolated incorporates and select the best components. The picked features are finally dealt with to bunch classifier for object course of action. The proposed method normally distinguishes and stamped object from endless model pictures with least human mediation. The proposed approach performs request under the oversaw procedure and achieves the best portrayal precision 93.8%, 88.6%, and near 100 percent on Caltech101, PASCAL 3D Additionally, and Barkley 3D dataset, which shows remarkable execution when stood out from existing methods.

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